Pushed Into Cleaner Energy: An Evaluation of the Household Well-being Impacts of Beijing's "Clean Heating Policy"

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Abstract

Burning of solid fuels for cooking, heating, and lighting threatens the environment, health, and development opportunities of one-third of the world's population. Transitioning to modern energy sources has been widely recognized as a key solution to these problems and a crucial step toward achieving sustainable development. This thesis comprises three manuscripts that examine China's efforts to promote energy transition in rural households.

In the first manuscript, I analyze the temporal trends and spatial characteristics of China's rural household energy transition over the past three decades based on administrative statistics. The results show a gradual but geographically uneven transition over the past three decades in China's rural household sector. A prediction model further illustrates that, compared to warmer provinces where a complete transition can be expected under a "business as usual" scenario, most northern provinces with intensive winter heating needs would see a low share of clean energy by 2050 without policy interventions. This chapter helps justify the rationale for a large-scale intervention targeting the rural household space heating energy transition.

To combat severe winter air pollution, Beijing implemented the *Clean Heating Policy* in rural areas since 2013, aiming to promote the household energy transition for space heating by banning coal burning and subsidizing the cost of heating equipment and the use of modern energy sources. The unaffordability of essential energy services, often termed "energy poverty," poses a significant challenge when households transitioning from solid fuels to more expensive modern energy sources. In the second manuscript, I provide quasi-experimental evidence on the impacts of the *Clean Heating Policy* on energy poverty. The analysis couples

primary field survey data on economic and physical measures of energy poverty from over 1,000 rural households in Beijing with difference-in-differences methods to isolate a causal link. I find that, under the government's generous subsidies, the *Clean Heating Policy* significantly improves the quality of rural households' space heating in terms of nighttime indoor temperature, the number of rooms regularly heated, and average heating duration, with minimal financial challenges. The heterogeneity analysis suggest that the financial burden was more pronounced for households in high-altitude villages, with poorer prior heating infrastructure, and lower wealth.

The household energy transition can impact many key aspects of quality of life. In the third manuscript, I examine the impact of the *Clean Heating Policy* on participants' subjective well-being. Using difference-in-differences estimations on the survey data, I find that the *Clean Heating Policy* significantly improves life satisfaction, while its impacts on satisfaction with living conditions and income are less pronounced. Additionally, the results suggest that younger, wealthier households and those in poorer health experience more substantial improvements in life satisfaction.

These papers provide new empirical evidence demonstrating the largely positive but distributed impacts of household energy transitions driven by the targeted intervention. Notably, these outcomes rely heavily on strict policy enforcement and substantial government subsidies.

Résumé

L'emploi de combustibles solides pour la cuisine, le chauffage et l'éclairage menace l'environnement, la santé et les opportunités de développement d'un tiers de la population mondiale. La transition vers des sources d'énergie modernes est largement reconnue comme une solution clé à ces problèmes et une étape cruciale vers un développement durable. Cette thèse comprend trois manuscrits qui examinent les efforts de la Chine pour promouvoir la transition énergétique des ménages ruraux.

Dans le premier manuscrit, j'analyse les tendances temporelles et les caractéristiques spatiales de la transition énergétique des ménages ruraux chinois au cours des trois dernières décennies, en me basant sur des statistiques administratives. Les résultats montrent une transition progressive mais géographiquement inégale pour les ménages ruraux Chinois au cours des trois dernières décennies. Un modèle de prévision montre en outre que, comparativement aux provinces plus chaudes où une transition complète peut être attendue sous un scénario "statut quo," la plupart des provinces nordiques, ayant des besoins intensifs en chauffage hivernal, ne connaîtraient qu'une faible part d'énergie propre d'ici 2050 sans intervention politique. Ce chapitre justifie la logique d'une intervention à grande échelle ciblant la transition énergétique pour le chauffage des ménages ruraux.

Pour combattre la grave pollution atmosphérique hivernale, Beijing a mis en œuvre la Politique de chauffage propre dans les zones rurales depuis 2013, visant à promouvoir la transition énergétique pour le chauffage en interdisant la combustion de charbon et en subventionnant le coût des équipements de chauffage et l'utilisation de sources modernes d'énergie. La "pauvreté énergétique," décrivant des services énergétiques inabordables, représente un

défi significatif lorsque les ménages transitionnent des combustibles solides à des sources d'énergie modernes plus coûteuses. Dans le deuxième manuscrit, je fournis des tests quasi-expérimentaux des impacts de la Politique de chauffage propre sur la pauvreté énergétique. Cette analyse couple des données primaires d'enquête de terrain et des mesures économiques et physiques de précarité énergétique pour plus de 1000 ménages ruraux à Beijing à l'aide de la méthode des doubles différences pour isoler un lien causal. Nous constatons que, grâce aux généreuses subventions gouvernementales, la Politique de chauffage propre améliore significativement la qualité du chauffage des ménages ruraux en termes de température intérieure durant la nuit, du nombre de pièces régulièrement chauffées et de la durée moyenne de chauffage, avec des défis financiers minimes. L'analyse de l'hétérogénéité suggère que la charge financière était plus prononcée pour les ménages dans les villages de haute altitude, avec une piètre infrastructure de chauffage intérieure et une richesse moindre.

La transition énergétique des ménages peut impacter de nombreux aspects de la qualité de vie. Dans le troisième manuscrit, j'examine l'impact de la Politique de chauffage propre sur le bien-être subjectif des participants. En utilisant des estimations issues de la méthode des doubles différences sur nos données d'enquête, je constate que la Politique de chauffage propre améliore significativement la satisfaction de vie, tandis que ses impacts sur la satisfaction des conditions de vie et des revenus sont moins prononcés. De plus, nos résultats suggèrent que les ménages plus jeunes, plus riches et en moins bonne santé connaissent des améliorations plus importantes de leur satisfaction de vie.

Cette thèse fournit de nouvelles preuves empiriques démontrant les impacts largement positifs, mais aussi distribués, des transitions énergétiques ménagères menées dans le cadre d'une intervention ciblée. Avant tout, ces résultats dépendent fortement d'une application stricte des politiques et d'importantes subventions gouvernementales.

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List of Abbreviations

PM	Particulate Matter
$PM_{2.5}$	Particulate Matter less than 2.5 micrometers in diameter
PM_{10}	Particulate Matter less than 10 micrometers in diameter
LPG	Liquefied Petroleum Gas
LSMS	Living Standards Measurement Survey
OECD	Organisation for Economic Co-operation and Development
BAU	Business as Usual
ARIMA	Autoregressive Integrated Moving Average
kgce	kilogram Coal Equivalent
NISP	National Improved Stove Program
CESY	China Energy Statistical Yearbook
TREM	Typical Rural Energy Model
CBESAR	China Building and Energy Saving Annual Report
CRSR	China Rural Statistics Report
AICc	Akaike's Information Criterion

MLE	Maximum Likelihood Estimation
EC-NE	Extreme Cold-Northeast zone
EC-NW	Extreme Cold-Northwest zone
EC	Extreme Cold zones
CW-YP	Cold Winter-Yangtze Plain zone
WW-S	Warm Winter-South zones
C-N	Cold-North zone
C-T	Cold-Tibet Plateau zone
C	Cold zones
DiD	Difference-in-Differences
CI	Confidence Interval
DALYs	Disability-adjusted Life-years
WHO	World Health Organization
TWFE	Two-way Fixed Effects
Exp	Winter Energy Expenditure
Temp	Nighttime Indoor Temperature
SD	Standard Deviation
Dep.var.	Dependent Variable
Num.Obs.	Number of Observations
Obs	Observations

FE Fixed Effect

T_Timing Cohort of Treatment Timing

PCA Principle Component Analysis

OLS Ordinary Least Square

ATT Average Treatment Effects on the Treated

SEPAP Solar Energy Poverty Alleviation Program

PV Solar Photovoltaic

AQI Air Quality Index

NFS No Fangshan Observations

NFS4 No Fangshan Season 4 Observations

KPSS Kwiatkowski–Phillips–Schmidt–Shin

IEA International Energy Agency

IRENA International Renewable Energy Agency

UNSD United Nations Statistics Division

CCA Clean Cooking Alliance

NECP National Efficient Cooking Program

“青山相待，白云相爱，梦不到紫罗袍共黄金带。一茅斋，野花开。管甚谁家兴废谁成败，陋巷箪瓢亦乐哉。贫，气不改；达，志不改。”

— [元] 宋方壶 ·《山坡羊 · 道情》

“Green mountains surrounded me, and white clouds embraced me, I have never longed for silk satin to adorn me. In my humble dwelling, wildflowers bloom in abundance. Regardless of who prospers or declines, I find contentment in my own modest life. Poverty cannot crush my spirit, and wealth will not alter my aspirations.”[1]

— [Yuan dynasty] Fanghu Song *Shanpoyang Daoqing*

[1]Translated by Xiang.

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Contribution to Original Knowledge

This dissertation uses a range of quantitative methods to examine the current situation and policy efforts of China's rural household energy transition. Overall, the primary contributions of this work arise from the collection of extensive and multi-modal primary data, the application and synthesis of recently developed empirical methods, and the impact evaluation of energy transitions in developing countries. Unlike the widely-studied cooking energy transition, this dissertation focuses on the less-studied household energy transition in space heating. In terms of empirical methods, considering the gradual implementation of the *Clean Heating Policy*, this dissertation demonstrates the practical application of available newly developed heterogeneity-robust difference-in-differences estimators. Regarding data, two chapters in this dissertation employ primary field survey data collected between 2018 and 2022, covering over 1,000 rural households in Beijing. This unique panel data enables more effective control of unobservable confounders compared to most existing studies on the *Clean Heating Policy*, which primarily rely on simple comparisons (i.e., before versus after or treated versus untreated) using cross-sectional data.

Specifically, the contributions of each chapter to original knowledge are as follows. **Chapter 2** investigates the temporal trends and spatial characteristics of China's rural household energy transition. By comprehensively collecting and integrating publicly available administrative statistics on rural household energy consumption, this chapter significantly extends the temporal scope of existing research through an analysis of historical data spanning the past 30 years. Across the categories of the China rural domestic energy use zones, our results clearly demonstrate the significant differences in progress between cooking and heating energy transitions. Furthermore, using time-series methods based on comprehensive administrative statistics, we forecast a counterfactual "business-as-usual" scenario for the *Clean Heating Policy*. **Chapter 3** examines the impacts of the *Clean Heating Policy* on household energy poverty, utilizing primary field survey data. This chapter reveals the one-sidedness and limitations of traditional economic measurements of energy poverty by integrating physical measurements of household space heating. It underscores the importance of assessing energy poverty through a comprehensive approach that considers both economic factors and the extent to which energy needs are met. **Chapter 4** investigates the impacts of the *Clean Heating Policy* on participants' subjective well-being. In this chapter, we prioritize the subjective evaluation of those households involved in the energy transition, enriching the current perspective on the objective impacts of what were believed to matter. This chapter contributes to the growing body of literature employing subjective well-being measures to inform public policy decisions. Moreover, this chapter introduces mediation analysis, a method more commonly employed in fields such as psychology and epidemiology, to facilitate an exploratory discussion on the mechanisms by which household energy transition impacts life satisfaction.

Contributions of Authors

I am the primary and lead author of all chapters in this dissertation. In Chapters 2, 3, and 4, I formulated the research questions and was responsible for data analysis, interpretation, and drafting the initial manuscripts. Brian Robinson and Chris Barrington-Leigh provided consistent guidance throughout the conceptualization, study design, data analysis, interpretation, and manuscript editing processes. Chapters 3 and 4 utilize data from the Beijing Household Energy Transition project. Initial support for this project came from co-supervisors Brian Robinson and Chris Barrington-Leigh. Additional and ongoing support has been provided by Jill Baumgartner and Sam Harper, current principal investigators of the project. Xiaoying Li and I supervised the field data collection. Talia Sternbach processed the raw indoor temperature data for Chapters 3 and 4, while Xiaoying Li processed the raw air quality data for Chapter 4.

Chapter 1

Introduction

1.1 Research objectives

A third of the world's population still burns solid fuels to meet household energy needs, with up to 95% of them living in the rural areas of developing countries (Bonjour et al., 2013; Bruce et al., 2015; Gordon et al., 2014; Hanna et al., 2016). This situation results in a series of negative impacts, including significant degradation of air quality, severe health damage, increased greenhouse gas emissions, and worsening gender equality (Beltramo & Levine, 2013; Boman et al., 2003; Ezzati & Kammen, 2002; M. A. Jeuland & Pattanayak, 2012; J. Liu et al., 2016; Pachauri & Jiang, 2008; Smith et al., 2004). In response, various interventions worldwide aim to facilitate transitions to cleaner energy sources. A key objective of these interventions is to achieve universal and affordable access to clean energy, as highlighted in Goal 7 of the 2030 Agenda for Sustainable Development (Vera & Langlois, 2007).

In northern China, severe air pollution during winter, primarily caused by atmospheric particulate matter with a diameter less than 2.5 micrometres ($PM_{2.5}$), has garnered widespread public attention in recent years (Huang, 2015; S. Wang et al., 2015). To combat this, the *Clean Heating Policy*, which has been in place since 2013, promotes the transition to cleaner energy sources for rural household space heating. This policy includes a series of measures: it prohibits the use of coal for space heating and offers subsidies for energy-efficient heating equipment, as well as for the costs associated with modern energy sources, such as electricity and natural gas (X. Zhang et al., 2019; Z. Zhang et al., 2017). This policy integrates command-and-control strategies with economic incentives to mandate the energy transition in rural households.

Beijing was selected as the pilot area to implement the *Clean Heating Policy* due to its advanced infrastructure and favorable socioeconomic conditions. By the end of 2022, the policy had been applied to 1.35 million households across 3,557 villages, covering 90% of Beijing's villages and 93% of rural households with clean heating solutions (Cao, 2023). Several studies have demonstrated that the *Clean Heating Policy* results in significant positive social net benefits from avoided health losses, supporting its economic viability at the regional level (Lin & Jia, 2020; Ma et al., 2023; Xie et al., 2019; X. Zhang et al., 2019). However, concerns such as environmental suitability, financial burdens on rural households, and inadequate space heating have impeded its expansion in remote mountain areas (China National Energy Administration, 2019; He & Li, 2020; L. Zhu et al., 2020).

Energy transition impacts various aspects of people's living circumstances. An increased reliance on clean heating often results in higher energy expenditures, which could impose a significant financial burden on households. Within the mandatory framework of the *Clean Heating Policy*, some households may struggle with the trade-off between thermal comfort and energy costs, potentially exacerbating energy poverty and affecting distributional equity. However, transitioning to cleaner fuels is expected to yield considerable benefits, including improved indoor air quality and health, as well as time savings from reduced fuel preparation. Despite these potential advantages, the overall perception of the *Clean Heating Policy*'s impact on people's lives remains an area that requires further investigation.

This paper aims to shed light on the current status of the energy transition and explore transition interventions for rural Chinese households by evaluating the well-being impacts of the *Clean Heating Policy*. Taking the *Clean Heating Policy* in Beijing as a case study, this dissertation is structured around three research questions:

RQ1: How does rural household energy transition in China unfold in the absence of policy intervention?

RQ2: How does the intervention in household energy transition impact energy poverty?

RQ3: What are the effects of energy transition on household subjective well-being?

In this dissertation, I explore three research questions in Chapters 2, 3, and 4, respectively. Chapter 5 discusses the findings, outlines the limitations, and proposes avenues for future research. Chapter 6 concludes the dissertation. In the remaining sections of this chapter, I conduct a literature review focusing on two primary subjects of this dissertation.

1.2 Relevant literature

In this section, I review literature relevant to the two main research topics of this dissertation: household energy transition and human well-being.

1.2.1 Literature on household energy transition

In this section, I will review several key aspects of household energy transitions, including the definition, contributing factors, and potential outcomes.[1] Central to this review is the exploration of the relationship between energy transition and poverty, which serves as a thematic thread to evaluate the potential impacts of energy transitions on households.

1.2.1.1 Defining patterns of household energy transition

The household energy transition refers to the significant shift from the use of primary fuels to modern energy sources for domestic purposes (Leach, 1992).[2] The classic "energy ladder" theory, as depicted on the left side of Figure 1.1, succinctly describes the progression of energy transition. It outlines a one-directional shift from primitive fuels — such as firewood, agricultural waste, and animal waste — toward transitional fuels like charcoal, kerosene, and coal, and ultimately to more advanced fuels including liquefied petroleum gas (LPG), electricity, and natural gas, accompanying improvements in socioeconomic status (Masera

[1] This section is a revised version of my response to a PhD comprehensive exam question.

[2] This section focuses on the energy transition for basic household energy needs including cooking, space heating, and lighting. Productive uses are not covered.

et al., 2000). This theory posits two key ideas: (1) households adopt more sophisticated fuels as their wealth increases, and (2) once households switch to cleaner fuels, they do not revert to using dirtier fuels.

However, especially regarding — fuel use for space heating — the reality often fails to validate the two viewpoints proposed by the energy ladder theory. One contributing factor is the variation in thermal comfort provided by different heating methods. The majority of households in rural northern China continue to use coal in stoves with radiator systems for space heating (Y. Chen et al., 2016). In contrast, poorer households may rely solely on portable electric heaters or electric blankets for bedtime heating, yet still suffer from low indoor temperatures that hardly constitute a comfortable living environment (Robinson et al., 2018). This situation results in poorer households potentially appearing higher on the energy ladder. Meanwhile, a small fraction of wealthier households have voluntarily abandoned dirty fuels to complete their transition to electric heating (Su et al., 2018). Indeed, although both the poorest and wealthiest households technically use electricity for heating, the context and quality of that usage vary significantly, leading to persistent significant disparities in their socioeconomic profiles.

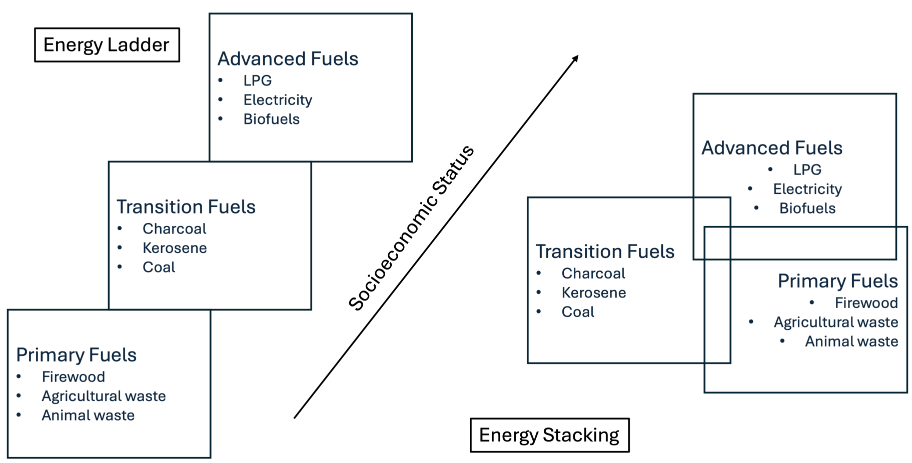

Figure 1.1: Energy ladder and energy stacking. This figure is an adaptation of Figure 2.1 from Van der Kroon et al. (2013).

While the high efficiency and cleanliness of advanced fuels are attractive, nostalgia for traditional fuels can often impede transitions away from them (Masera & Navia, 1997; Nansaior et al., 2011). A dataset covering 246 households from 1995 to 2015 in Beijing indicates that although 90% of the sample households adopted clean energy for space heating over the past 20 years, only 9% completely ceased using solid fuels (Carter et al., 2020). In contrast to the "energy ladder" theory, the "energy stacking" theory — illustrated on the right side of Figure 1.1 — has been proposed as an alternative model in discussions of energy transition in developing countries (Cheng & Urpelainen, 2014; Heltberg, 2005). This theory suggests that household energy transitions are typically mixed, involving the continuous use of dirty fuels alongside the adoption of modern energy sources (Shankar et al., 2020; X. Zhu et al., 2018).

1.2.1.2 Factors influencing household energy transition

Even though the "energy ladder" and "energy stacking" theories concisely summarize the driving force behind household energy transitions as improvements in socioeconomic status, this improvement actually encompasses a series of interrelated factors. Van der Kroon et al. (2013) proposes a conceptual framework categorizing these factors into three layers: (A) the external socio-cultural and natural environment, (B) the external political-institutional-market environment, and (C) the households' internal opportunity set. Using this framework, this section will explore the factors influencing household energy transitions.

(A) External socio-cultural and natural environment. This layer comprises four types of factors: nature and ecology, geographic location, history, and the international economic system. Nature and ecology, along with geographic location, physically determine the demand for and availability of fuel in a region. For instance, higher latitudes and altitudes result in colder winter temperatures, thereby increasing the demand for space heating (Auffhammer & Mansur, 2014; Deroubaix et al., 2021). In regions without district heating systems, households often rely on individual heating systems that combust fuels to generate thermal comfort (Pavlović et al., 2021; L. Zhu et al., 2020). Additionally, the regional availability of specific fuels — such as natural gas in Russia and biomass in Nordic countries — naturally influences their adoption (Korppoo & Korobova, 2012; Parikka, 2004).

Historical factors also play a significant role, as they shape cultural traditions and habits in fuel use. Some household energy intervention programs have failed when new technologies did not align with local cooking needs and style preferences (Diehl et al., 2018; Jagger & Das, 2018).

(B) External political-institutional-market environment. This middle layer can be seen as a social functioning profile, illustrating how macroeconomic factor markets interact under the influence of government policies and societal values. These interactions ultimately determine the prices and allocation of energy resources. A key component within this layer is the consumer goods market, which directly impacts the access, stability, and price of energy sources. As of 2021, 8.6% of the world's population lacked access to electricity and clean cooking fuels,[3,4] respectively (IEA et al., 2023). The majority of these individuals reside in developing countries within Africa and Asia (Ritchie et al., 2024). Price stability and reliable supply are paramount concerns even for those with access to modern energy, influencing their continued use (Hasselqvist et al., 2022; Pattanayak et al., 2019). Recent events like the COVID-19 pandemic and the Russo-Ukrainian War in 2022 have exacerbated energy crises, leading to soaring energy prices and shortages, particularly of natural gas (Guan et al., 2023). This has prompted households in developed nations such as Germany and Sweden to revert to firewood for heating (Laakso et al., 2024). Government policies that promote energy transitions often focus on improving access, ensuring stable supply, and managing prices through infrastructure upgrades and subsidies (Aung et al., 2021; Guta et al., 2022; Quinn et al., 2018).

(C) Households' internal opportunity set. The innermost layer concerns the household's internal opportunity set. Attributes such as socioeconomic and demographic characteristics shape a household's preferences, perceptions, and ability to access and afford modern energy (Aguilera et al., 2024; Ruokamo, 2016). Specifically, the assets a household owns define the budget constraints for energy decisions, with wealthier households typically having a

[3] Access to electricity is defined in international statistics as having a source of electricity that can provide very basic lighting, charge a phone, or power a radio for 4 hours per day.

[4] Clean cooking fuels and technologies refer to non-solid fuels such as natural gas, ethanol, or electric technologies.

broader choice of fuels and technologies (Behera & Ali, 2016; Rahut et al., 2019). Technological barriers, such as knowing how to correctly use and maintain new equipment, also pose significant challenges, particularly for those lacking information or the capacity to process it (Hanna et al., 2016; Seguin et al., 2018; Steg, 2008). Household internal attributes are a central focus in empirical studies investigating factors influencing energy transitions. Factors found to positively affect the adoption of clean energy include having a female household head, education level of the household head, income, health status, and the presence of children at home. In contrast, residing in rural areas, agricultural and forest land area, being self-employed, the age of the household head, and larger family size are typically associated with reduced clean energy use (Ekholm et al., 2010; Lewis & Pattanayak, 2012; Mensah & Adu, 2015; Song et al., 2018; X. Zhu et al., 2022). However, these empirical results are often mixed and highly context-dependent.

1.2.1.3 The relationship between household energy transitions and poverty

As a fundamental component of basic living needs, the quality of energy services accessible to households directly affects their overall quality of life. The widely influential Multidimensional Poverty Index (MPI) in policy research explicitly includes access to cooking energy and electricity services as part of the measurement of a country's poverty index (Alkire et al., 2018). In this section, I will discuss some of the anticipated impacts households may face during the energy transition, noting how poverty may impact decision-making along the way.

Financial Impacts. The relationship between energy transition and poverty is complex. On one hand, energy expenditures constitute a substantial portion of a household's budget, representing the most direct interaction between energy use and poverty (Boardman, 2013; Heltberg, 2003). For those overwhelmed by the cost of adequate energy services, an increase in energy expenditure could significantly threaten their financial stability or their ability to meet basic energy needs (Wright, 2004). According to Guan et al. (2023), the energy price increases triggered by the Russo-Ukrainian War are estimated to raise total household energy costs by between 62.6% and 112.9%, potentially pushing an additional 78 million to 141 million people into extreme poverty. Modern energy sources are typically more expensive than solid fuels, leading to an inevitable increase in household energy expenditures (Polsky & Ly, 2012). In rural northern China, a comparison of various heating options reveals that the annual cost of clean heating methods, such as air source heat pumps or natural gas heaters, is at least twice that of burning coal in traditional stoves when no government subsidies are applied (H. Liu & Mauzerall, 2020). Additionally, the initial one-time investment required for a stove that aligns with energy transitions represents a significant expense (M. A. Jeuland & Pattanayak, 2012). Consequently, the energy transition could further exacerbate household poverty (Nguyen et al., 2019).

On the other hand, the multidimensional outcomes of household energy transitions could potentially enhance family income and alleviate poverty (Andadari et al., 2014; Cabraal et al., 2005; Heltberg, 2004). The impact of electricity access on reducing household poverty has garnered significant attention within this field (Kanagawa & Nakata, 2008). Although many studies have examined the direct impact of electricity access on household income and poverty reduction through the productive use of electricity, such as enhancing agricultural production efficiency and creating employment, these topics are beyond the scope of this section (Khurana & Sangita, 2022; Pueyo & Maestre, 2019; Willcox et al., 2015). Hutton et al. (2006) categorizes the potential positive outcomes of energy transitions for basic domestic uses into three broad categories: direct health-related impacts (including health effects, health expenditures, and income effects related to health), direct non-health-related impacts (such as time impacts and household environment improvements), and indirect environmental impacts (both local and global). This section will focus on the first two categories, exploring how household energy transitions can contribute to lifting households out of poverty.

Health-related impacts. Good health is essential for engaging in agricultural activities, operating small businesses, or working for wages (Croppenstedt & Muller, 2000; Schulte & Vainio, 2010). Additionally, medical expenses for treating illnesses significantly contribute to pushing families into poverty (Y. Liu et al., 2003; Van Doorslaer et al., 2006). The substantial health hazards associated with the preparation and burning of solid fuels often drive the pursuit of energy transitions (Ezzati & Kammen, 2002; Rehfuess & World Health Organization, 2006). The health benefits of transitioning to cleaner energy sources primarily stem from reduced exposure to household air pollution, fewer accidents from open fires, and decreased risks associated with fuel collection (Hutton et al., 2006).

Household air pollution from burning solid fuels has become a leading health risk factor in developing countries (Feigin et al., 2016). Solid fuels burned in traditional stoves emit complex air pollutants, including particulate matter (PM), carbon monoxide, and volatile organic compounds (Franklin, 2007). The average 24-hour indoor PM_{10}[5] concentrations in households using solid fuels in developing countries can exceed WHO recommended standards by 6 to 66 times (Rehfuess et al., 2011; World Health Organization, 2021). Exposure to such pollution significantly increases the risk of morbidity and mortality from respiratory diseases like chronic obstructive pulmonary disease and lung cancer, as well as cardiovascular diseases (Gordon et al., 2014; Lee et al., 2020). In 2021, household air pollution was responsible for over 3.1 million premature deaths worldwide, with the highest impacts observed in India, China, and Indonesia (Global Burden of Disease Collaborative Network, 2020). The large-scale Improved Stove Program, initiated in rural China during the 1980s, represents a significant health intervention aimed at reducing household air pollution. By 2014, this program was estimated to have decreased indoor $PM_{2.5}$ concentrations by 30% and premature deaths attributable to residential emissions by 37% (Meng et al., 2021).

Besides the impacts from less exposure to household air pollution, energy transition could improve people's health by less accidents with open fire and hazards related to fuel collection (Johnson & Bryden, 2015). Combustion of solid fuels in open stoves is a major cause of burn injuries in less developed countries (Albertyn et al., 2012). In India alone, there are over 700,000 burn admissions annually (Ahuja & Bhattacharya, 2004). The collection and transportation of biomass fuels can lead to injuries from falls, cuts, and attacks by wild

[5]Particulate matter of a diameter of up to 10 micrometers.

animals, as well as miscarriages due to carrying heavy fuel loads (Haile, 1991; Oluwole et al., 2012).

The transition to modern energy sources for cooking, heating, and lighting can significantly improve household air quality (T. Li et al., 2016; Sidhu et al., 2017), reduce health risks (Puzzolo et al., 2024; Quansah et al., 2017; Smith & Pillarisetti, 2017), and decrease labor loss due to sick days (Stabridis & van Gameren, 2018), as well as medical expenditures (Lin & Wei, 2022; Rahut et al., 2017). Consequently, the health benefits derived from household energy transitions can enhance productivity, boost family income, and ultimately assist families in escaping poverty (Schultz, 2005).

Non-health related time impacts. Besides the time-saving impacts from health-related factors previously discussed, household energy transitions could also free up time for productive activities due to various non-health-related factors (M. B. Malla et al., 2011).

Energy transition can significantly reduce cooking hours through enhanced efficiency (Petrokofsky et al., 2021). Rural women in developing countries typically devote 2 to 5 hours per day to cooking with solid fuels, which is the most time-consuming daily activity apart from sleeping (Chakraborty et al., 2014; Das et al., 2017; Romieu et al., 2009; Zaman, 1995). Switching to modern energy sources, such as LPG, can save about 50% of the time currently spent on food preparation (Christiaensen & Heltberg, 2014; Jagger et al., 2019; A. K. Malla et al., 2011). Additionally, replacing biomass with modern energy sources can also decrease the time burden associated with fuel collection, which can be considerable depending on local demand and availability of firewood. For instance, a study covering 274 villages in Nepal found that each household spends about 8 hours per week collecting firewood (Baland et al., 2010). Similar findings have been reported in Sub-Saharan Africa (Adkins et al., 2012; Brouwer et al., 1997). The time saved through efficient cooking and reduced fuel preparation not only provides opportunities for engaging in productive activities but also promotes an increase in household income (Calzada & Sanz, 2018; Martey et al., 2022).

Women and children typically bear the responsibility for collecting and using fuel, making energy transitions critical for improving their health and providing developmental opportunities (Jagger & Shively, 2014; James et al., 2020; Po et al., 2011). For children, access to electricity and the reduction of housework burdens can significantly enhance their educational access and academic performance, addressing key underlying causes of poverty (Choudhuri & Desai, 2021; Nazif-Muñoz et al., 2020; Squires, 2015; Y. Zhang et al., 2023). In addition to being related to the important sustainable development goals, such as poverty eradication, health, education, job and gender equality, the household energy transition will have a profound impact on sustainable development through climate, sustainable cities, food security and more (Pham-Truffert et al., 2020; Pradhan et al., 2017).

1.2.2 Literature on human well-being measures

To understand the impact of household energy transitions on well-being, it is important to consider how we can characterize and measure ideas of the human condition. Therefore, in this section, I review the literature related to human well-being, another research object of this dissertation, with an emphasis on its various measures.[6] The discussion will cover several pivotal issues in the measurement of human well-being. These include interpersonal comparisons of human well-being, the validity and limitations of using income as a proxy for well-being, extensions that aim to capture human well-being in multidimensional measures, and the comparison of these methods with subjective well-being.

1.2.2.1 Interpersonal comparison of human well-being

Well-being, often expressed as a reflection of a good living state, is widely recognized as a crucial goal across various fields, including development and public policy (Austin, 2020; Stiglitz et al., 2009). Despite its extensive application, well-being is an abstract concept lacking a unified, clear definition, leading different disciplines to highlight particular facets

[6] This section incorporates a revised version of my response to a PhD comprehensive exam question, in accordance with the supervisory committee's recommendations.

(McGillivray & Clarke, 2006). In psychology, well-being is typically associated with positive mental states such as pleasure, happiness, and satisfaction (Winefield et al., 2012). Health-related research focuses on comprehensive physical and mental health, while economic studies often equate well-being with wealth or the satisfaction of preferences (utility) (Alexandrova, 2017; Jarden & Roache, 2023; White et al., 2019). Although these perspectives vary, they all evaluate individuals' living conditions. Reflecting the broad scope of this evaluation, which encompasses the entirety of life rather than isolated aspects, I define well-being as a global assessment covering all dimensions of a person's life (Diener, 2009; Gasper, 2007).

Depending on the perspective from which life is evaluated, the definition of well-being can be categorized into objective well-being and subjective well-being (Sumner, 1996). Objective well-being is assessed from an external standpoint, focusing on universally desirable life features regardless of an individual's personal feelings or experiences (Diener, 2009). It is grounded in the belief that certain objective conditions are essential for a high-quality life (Adler & Fleurbaey, 2016). Although it is impractical to enumerate every aspect relevant to life quality, researchers aim to identify the most critical domains (Alatartseva & Barysheva, 2016; Kammann, 1983; Voukelatou et al., 2021). For example, the OECD's *How's Life 2020: Measuring Well-being* report highlights several such domains, including health, environment, employment, wealth, and safety (OECD, 2020). In contrast, subjective well-being requires an individual to evaluate their entire life, taking into account personal interests, preferences, and needs (Diener, 2009; Shin & Johnson, 1978). Diener (1984) summarizes three hallmarks of subjective well-being: it is inherently subjective as it resides within the individual's experience, involves positive evaluations, and typically encompasses a global assessment of all life aspects.

Interpersonal comparisons of well-being are crucial when utilizing well-being measures to inform public policy, particularly when considering the distributive effects of resource allocation (de Boer, 2024). When distributing limited resources, it is essential to prioritize groups that would either gain the most from improvements in well-being for efficiency reasons or those currently experiencing the lowest levels of well-being to uphold principles of justice (Elster & Roemer, 1993; Harsanyi, 1990; Rawls, 1971). The essence of interpersonal comparability lies in its ability to gauge the differential impacts of policies on the population's average well-being, acknowledging that some policies may advantage certain individuals while disadvantaging others (Mueller, 2003; Ng, 2008). Under the framework of objective well-being, comparing individuals' well-being appears straightforward: an individual in a more favorable state across key well-being domains is considered better off than one in a disadvantaged state. For instance, generally, a person in robust health experiences higher well-being than someone dealing with severe illness. Similarly, an individual with substantial income or living in an area with pristine environmental conditions typically enjoys a better quality of life than someone struggling with poverty or residing in a polluted area. However, when these comparisons involve multiple well-being domains simultaneously, complexities arise. The challenge lies in developing a unified metric that accurately reflects well-being across diverse dimensions. Despite these complexities, as long as there is a common understanding of what constitutes "good" in these dimensions, such comparisons are generally considered acceptable.

The inclusion of subjective factors such as personal preferences in defining subjective well-being introduces significant complications in making interpersonal comparisons. For example, the divergent reactions of optimists and pessimists to the same life events can vary their perceived well-being significantly. Particularly in economics, where well-being is equated with utility, most economists contend that inter-personal comparisons of well-being are impractical due to their inherently introspective nature (Hausman, 1995; Robbins, 2007). Since such subjective judgments cannot be observed or "scientifically" measured, people often reject making these comparisons and consider them meaningless (Sen, 1997; Suzumura, 1996). In the context where ordinal utility theory prevails, people can only infer the ranking of utilities in different scenarios based on observed choices. However, the magnitude of utility differences between scenarios remains unknowable, and comparisons of utility between individuals are not even feasible (Gibbard, 1986; Miller, 2008; Ng, 1997).

This dilemma compromises the interpersonal comparability of subjective well-being, which holds considerable practical significance for shaping public policy. However, it is considered meaningless because it cannot be scientifically assessed, particularly in the field of economics. However, in reality, interpersonal comparisons of welfare are quite common. For instance, when comforting a friend in despair, people might say, “Your life is still much better than many people’s.” Although this might simply be intended as consolation, it actually involves evaluating our friend’s life situation and comparing it with that of others. This occurs because people are empathetic and share a common understanding of what is well-being (de Boer, 2024; Harsanyi, 1979). Ferrer-i-Carbonell and Frijters (2004) reviewed two psychological findings that support the interpersonal comparison of well-being: first is that to a certain extent, people can perceive the well-being level of others. For example, people can accurately recognize the emotions of others, and this also holds true across cultures (Ekman & Friesen, 2003; Sandvik et al., 1993). Second, within the same cultural context, people can translate terms that describe well-being states into approximate numerical measures for communication (Van Praag, 1991).

The consistency in how people perceive situations, such as indicated by the similar perception and expression of physical pain in different individuals, provides a basis for comparing interpersonal well-being (Kahneman, 2000). Moreover, since empirical research typically focuses on average well-being at the population level, impacts from personal traits are further mitigated (Fabian, 2019; Stutzer & Frey, 2010). In fact, subjective well-being, measured in terms of life satisfaction or happiness measured (thus compared) in a given cardinal interval, has been widely used in psychology and as an indicator of national or regional progress (Fleurbaey & Blanchet, 2013; MacKerron, 2012). A series of correlation analyses with objective measurements like suicide rate and physical health provide empirical evidence for comparability (Frijters et al., 2020; Koivumaa-Honkanen et al., 2001).

In this section, I review several definitions of well-being and discuss the validity of interpersonal comparability of well-being, under both objective and subjective definitions. Although some economic studies narrowly define well-being as utility and reject interpersonal comparisons under ordinal utility theory, the concept of interpersonal comparison finds ready acceptance in broader research fields and plays a crucial role in practical applications.

1.2.2.2 Income as a proxy of human well-being

Everyone requires an adequate income to cover essential living expenses, such as food and housing, highlighting the crucial role of income in determining an individual's living status (Chetty et al., 2016). Additionally, income-based measures have commonly served as indicators for assessing personal living conditions or regional development because they are concise and easy to measure (Brinkman & Brinkman, 2011). In this section, I will explore the rationality and limitations of using income as a proxy for well-being, considering both its objective and subjective definitions. Before delving into a detailed discussion, it is crucial to establish that the validity of using income-based measures as proxies for well-being assumes a monotonic relationship between the two. This implies that as income — whether individual income or GDP at the regional level — increases, the level of well-being should also continuously increase. If this is not consistently the case, it suggests inherent limitations in using income as a measure of well-being.

Income growth can enhance people's "capacity" to attain a better state in key dimensions of objective well-being, especially when their current conditions are deficient (Kuklys & Robeyns, 2005). The most critical link between increased income and objective well-being is the fulfillment of basic material needs (Sullivan et al., 2008). Higher incomes improve the affordability of essential resources such as food and housing, thereby reducing the risk of hunger and ensuring residential security (Casey et al., 2001; Gundersen & Ziliak, 2018; Hulchanski, 1995; Veenhoven, 1991). Beyond fulfilling material needs, the literature on objective well-being and quality of life also extensively discusses the relationship between income and the satisfaction of other non-material needs (Gasper, 2005). For instance, as incomes rise, improved nutrition and better living conditions, coupled with more affordable access to medical care, can significantly enhance people's health (Ettner, 1996; Marmot, 2002). Regarding education, an increase in household income can free individuals, particularly children, from domestic labor, thereby enhancing their access to schooling and improving their academic performance (Bastagli et al., 2019). Moreover, when income is sufficiently high, individuals can choose their living environments by relocating to areas with better environmental quality and can more easily achieve a work-life balance or even opt not to work at all (Bridgman et al., 2018; Z. Liu & Yu, 2020; Qin & Zhu, 2018). Bick et al. (2018), based on an internationally comparable database, indicate that adults in low-income countries work 50% more hours per week than those in developed countries. Within countries, the data also show that higher incomes correlate with reduced working hours, particularly in the poorest nations.

The discussion above demonstrates that increases in income play a significant role in enhancing key aspects of objective well-being. However, evidence suggests that increases in income do not necessarily lead to continuous improvements: some aspects do not improve beyond a certain income level, and in some cases, increased income may even have negative effects. Gasper (2005) notes that after reaching a middle-income level, further income growth may not lead to substantial improvements in areas such as education and health; after all, one cannot achieve literacy twice, nor can one live indefinitely. Moreover, the increase in income may come at the expense of some key areas of well-being. For example, in the pursuit of higher income, individuals may work longer hours, experience increased mental stress, compromise their health, and strain their social relationships (Bannai & Tamakoshi, 2014; Chan, 2009; Cygan-Rehm & Wunder, 2018; Valcour, 2007; F. Zhang et al., 2023). Besides the individual examples discussed above, the environmental Kuznets curve, demonstrates that in a region's early development stages, increases in income often come at the cost of worsening environmental quality (Dinda, 2004). The cases discussed above challenge the validity of using income as a proxy for objective well-being.

I will now proceed to examine the relationship between income and subjective well-being. In reality, the vast majority of people pursue higher incomes; thus, it is reasonable to infer that they believe an increase in income improves their lives. In economics, utility theory suggests that as income increases, people can afford more and better options for consumption.

This moves them to a higher indifference curve, which represents an increased level of utility or well-being (Ferrer-i-Carbonell, 2005).

The well-known Easterlin Paradox has prompted a significant reevaluation of the relationship between income and subjective well-being. It suggests that while cross-sectional data indicate a positive correlation between income and happiness both within and across countries, this correlation does not persist over the long term as incomes grow within countries (Easterlin, 1974; Easterlin et al., 2010). Although some empirical results continue to support a positive correlation between income and well-being, the consensus among most studies is that increases in income levels only enhance subjective well-being to the extent that basic needs are met (Diener & Biswas-Diener, 2002; Gardner & Oswald, 2007; Stevenson & Wolfers, 2013). Beyond this threshold, the impact of income on well-being becomes very weak (Mentzakis & Moro, 2009). These findings suggest that income can serve as an effective proxy for subjective well-being within certain limits, particularly in scenarios where severe basic needs are unmet.

Several theories attempt to explain the weak correlation between income and subjective well-being (Wolbring et al., 2013). The first theory, based on Maslow's hierarchy of needs, suggests that once basic requirements such as food and housing are satisfied, individuals develop higher-level, non-material needs related to self-actualization, which are difficult to fulfill solely through increases in income (Diener, Horwitz, & Emmons, 1985; Maslow, 1943). The second theory posits that subjective well-being is influenced more by relative income, due to social comparison effects, than by absolute income (Blanchflower & Oswald, 2004; McBride, 2001). This is because people often use others as benchmarks when assessing their own well-being (Diener, 2009). As the economy grows and everyone's absolute income rises, subjective well-being may not improve if relative income positions remain unchanged (Diener & Fujita, 2013; Posel & Casale, 2011). The third theory focuses on adaptation (Di Tella et al., 2010). Adaptation mechanisms allow individuals to adjust their expectations about the impact of income on subjective well-being (A. E. Clark, 2016). Once people reach a certain income level, maintaining the same level of happiness typically requires continuous increases in income (Layard, 2011).

In this section, through a review of the relationships between income and both objective and subjective well-being, it is evident that income can serve as an effective proxy within certain limits, particularly when basic needs are unmet. However, once these limits are exceeded, the validity of using income as a proxy becomes questionable.

1.2.2.3 Multidimensional measures of human well-being

An implicit yet unexpressed issue in the previous discussion about using income as a proxy for well-being is the inherent limitation of relying on a single measure to capture the multidimensional nature of well-being (Chakravarty, 2017). To overcome this limitation, it has been proposed to assess well-being through multiple dimensions (Harkness, 2007). In this section, I will discuss the multidimensional measurement of well-being.

The capability approach, developed by Amartya Sen, provides the theoretical foundation for measuring well-being in a multidimensional context (Basu, 1987). This approach redefines the relationship between wealth and well-being by introducing the concepts of "Capability" and "Functions" (Gasper, 2002). Here, "Functions" refer to the "beings and doings" — the achievements of an individual manages to be or to do (Robeyns, 2003; Sen, 1999). "Capability," on the other hand, represents the set of all potential functionings available to a person, indicating the opportunities they have to realize these functions (Distaso, 2007; Gore, 1997). According to this approach, well-being should focus on the extent to which individuals are able to utilize goods and services to achieve desired functionings, rather than on the accumulation of wealth itself (D. A. Clark, 2005; Sen, 1990). Wealth is deemed important not for its own sake, but because it enables individuals to achieve their functionings (Sen, 1986).

According to Sen's theory, many efforts have been made to identify key capabilities that facilitate human functionings, employing multidimensional social indicators (Diener, 2009; Robeyns, 2006). As early as 1990, the annual Human Development Report recognized that human development is “a process of enlarging people’s choices” beyond mere wealth growth (United Nations Development Programme, 1990). It further identified “leading a long and healthy life, to be educated and to enjoy a decent standard of living” as the three essential dimensions of human development. Specifically, life expectancy at birth, expected years of schooling and mean years of schooling, and gross national income per capita are indicators for these three dimensions (Lind, 2019). Another example of a multidimensional indicator is the OECD’s Better Life Index, which examines a broad range of dimensions beyond income, education, and health. It includes housing, work, civic engagement, work-life balance, community, environment, safety, and even subjective well-being measure of life satisfaction (Mizobuchi, 2014). Furthermore, various other objective list approaches rooted in the concept of multidimensional well-being measurement, such as the Social Progress Index and the Canadian Index of Wellbeing, are utilized to assess well-being and development (Michalos et al., 2010; Porter et al., 2014).

Comparing the three concise dimensions of the Human Development Index with the eleven complex dimensions of the Better Life Index highlights two major challenges in multidimensional well-being measurement: deciding what domains to include and determining who should make those decisions (Diener, 2009). The determination of which domains to include inevitably involves a trade-off between covering as many domains as possible (though not exhaustively) and maintaining practical operability (Martinetti, 2000). This process, whether it relies on brainstorming or deductive theory-based methods, necessitates subjective human judgment, which may lead to paternalistic measures that are disconnected from individual experience (Amendola et al., 2023; Diener, 2009; Engerman, 1997). In addition, due to varying cultural backgrounds and developmental stages across countries, there are inherent differences in prioritized domains, making it challenging to establish universal indicators (Harkness, 2007; Kanbur, 2002). In practice, most multidimensional measurements of well-being involve aggregating indicators from various domains as an index. The selection, measurement of specific indicators, determination of their weights, and the methods of aggregation all present operational challenges to this type of measurement approach (Chowdhury & Squire, 2006; McGillivray, 1991; Srinivasan, 1994).

1.2.2.4 Subjective well-being

While some multidimensional approaches, such as the Better Life Index, incorporate measures of subjective well-being, they predominantly align with definitions of objective well-being. The most significant characteristic of subjective well-being is that it is derived from an individual's own experiences and evaluations of their life. Therefore, this approach potentially offers a much broader measurement compared to objective indicator methods, which are limited to domains of life observable by others (Diener, 2009, p.46). As subjective well-being has been defined in Section 1.2.2.1 as a global evaluation encompassing all aspects of a person's living situation, this section will focus on its measurement.

The pursuit of happiness and satisfaction with one's life is a common goal among the vast majority of people worldwide (Frey et al., 2010; J. Helliwell, 2012). Higher levels of subjective well-being not only enhance individuals' feelings about their lives but also confer several practical benefits. These include fostering creative thinking, enhancing health, improving work efficiency, and strengthening social relationships (DiMaria et al., 2020; Frey, 2011; Lyubomirsky et al., 2005; Maddux, 2025). At the beginning of this paragraph, I used the terms "happy" and "satisfied" to describe subjective well-being, reflecting its multifaceted structure that encompasses both related yet distinct affective and cognitive components (Lucas et al., 1996; Schimmack, 2008; Tov & Diener, 2013).

Specifically, the affective components of subjective well-being include positive affects such as joy and happiness, and negative affects such as sadness and depression. The cognitive components, on the other hand, encompass life satisfaction — pertaining to past, current, and future life — and domain satisfaction, including areas like work and finances (Diener et al., 1999). The difference between affective well-being and cognitive well-being lies in their focus on distinct aspects of subjective experience. Affective well-being centers on the emotional aspects of everyday experiences, while cognitive well-being involves an individual's reflective evaluation about their life as whole or within specific life domains (Chamberlain, 1988). Compared to affective well-being, cognitive well-being relies more on the living circumstances and is more stable (Diener et al., 2010). Therefore, it can better reflect the overall and continuous conditions of life, making it more suitable for assessing and informing public policy (J. F. Helliwell & Barrington-Leigh, 2010). My subsequent discussion of subjective well-being will focus exclusively on the measurement of cognitive well-being, specifically life satisfaction.

Most measures of subjective well-being rely on respondents' self-reported life satisfaction (Pavot & Diener, 1993). People are asked to evaluate their whole life or a specific domains (Van Hoorn, 2008). However, compared with the satisfaction with specific life domains, the overall life satisfaction is much more common (J. F. Helliwell & Barrington-Leigh, 2010). This phenomenon is caused by similar problems in multidimensional well-being measurement discussed in Section 1.2.2.3, particularly the trade-off between comprehensiveness and efficiency when selecting which domains to include, and the complexities involved in determining the weights for aggregating satisfaction across various domains (Margolis et al., 2019).

The overall life satisfaction question is usually framed as "All things considered, how satisfied are you with your life as a whole these days?" (Diener et al., 2013). Respondents are asked to rate their satisfaction using integers on various scales, where the lowest number represents "Completely/Very Unsatisfied" and the highest "Completely/Very Satisfied" (van Beuningen, 2012). These scales generally include 1–5 (e.g., China Family Panel Survey), 1–7 (e.g., UK Household Longitudinal Study), 1–10 (e.g., Statistics Canada's General Social Survey and World Values Survey), and 0–10 (e.g., Gallup World Poll) (Charles et al., 2019; Diener & Tay, 2015; Han & Gao, 2020; Ngamaba & Soni, 2018). To enhance data quality, modern life satisfaction measures typically employ an 11-point scale from 0 to 10, with this range chosen to enhance data quality (Kroh, 2006; OECD, 2013). Unlike traditional Likert-style response, this scale does not provide verbal cues for points other than the highest and lowest, effectively transforming the measure into a continuous numerical scale (Barrington-Leigh, 2024).

Although it is a relatively new research area, studies on subjective well-being in China have been gradually increasing (Abbott et al., 2016). Questions related to life satisfaction and happiness have also been progressively incorporated into large-scale household surveys in China (An et al., 2023; K. Zhang et al., 2022). According to the World Happiness Report powered by Gallup, China's average happiness index for 2021–2023 was 5.97 on 0–10 scale, ranking 60th among all countries (J. F. Helliwell et al., 2024). Based on World Values Survey data, Easterlin et al. (2012) found that life satisfaction in Chinese population exhibited an inverted U-shape from 1990 to 2010, with a decline from 1990 to around 2000–2005, followed by an upward trend. In the second decade of the 21st century, W. A. Clark et al. (2019) observed a continuous increase in life satisfaction and a narrowing gap in life satisfaction between rural and urban populations based on data from the China Household Finance Survey. Knight et al. (2009) indicates that for most households living in rural China, the impact of their relative position in the village's income distribution on life satisfaction is greater than that of absolute income, as they tend to limit their reference group to a narrow, village-level scope. Additionally, expectations regarding future income changes compared to past income, as well as perceptions of the quality of community public services and infrastructure, play a significant role in shaping life satisfaction among rural Chinese households.

Since the measurement of subjective well-being is based on self-reports and therefore difficult to verify, its reliability and validity are major concerns (Diener, 2009, p.67). Reliability refers to the consistency of measurement results. The reliability of self-reported measures is assessed in two main ways: first, by evaluating the consistency of outcomes for the same concept across different items and scales; and second, by determining the stability of results over time under unchanged conditions (Diener et al., 2013). Measurements based on different scales and various life satisfaction wording typically show moderate to high correlation (Lyubomirsky & Lepper, 1999; Pavot et al., 1991; Taormina & Gao, 2013). Additionally, life satisfaction exhibits relatively strong consistency over extended periods, spanning several months and even years (Diener, Emmons, et al., 1985; Krueger & Schkade, 2008). Krueger and Schkade (2008) conducted a test-retest analysis on the subjective well-being of 229 female participants with a two-week interval between measurements. The results revealed a correlation coefficient of 0.6 for life satisfaction between the two tests. Based on a meta-analysis of 83 correlation coefficients from 38 independent samples, the retest correlation coefficients ranged from 0.24 to 0.87. Notably, the correlation coefficients for periods within five years remained above 0.5 (Schimmack & Oishi, 2005). Over longer periods, the correlation coefficient tends to decrease due to significant changes in life circumstances (Fujita & Diener, 2005; Steger & Kashdan, 2007).

Reliability is a prerequisite for validity in measurements, but it does not imply validity (Pavot, 2013). Validity concerns "whether a well-being measure actually assesses well-being" (Diener, 2009, p.75). Diener (2009) outlined four key aspects to evaluate the validity of subjective well-being measurements: face validity (how closely a measurement appears to assess what it purports to measure), content validity (the extent to which a measure accurately represents the full breadth of the concept), convergent validity (how well the results from one measure of well-being align with results from other measures), and discriminant validity (the degree to which a measure does not reflect related but different constructs).

I will now provide a brief overview of the empirical evidence concerning content validity and convergent validity. Many empirical studies have shown that overall life satisfaction is strongly correlated with satisfaction in major life domains, suggesting that overall life satisfaction is a valid summary of domain-specific satisfaction (McAdams et al., 2012; Milovanska-Farrington & Farrington, 2022; Pavot & Diener, 2008; Rohrer et al., 2024). Van Praag et al. (2003) utilized structural models to analyze the relationships between overall life satisfaction and domain-specific satisfactions, including job, finances, housing, health, leisure, and environment, using data from the German Socio-Economic Panel which surveyed 20,000 individuals from 1992 to 1997. The results demonstrate that overall satisfaction effectively incorporates various domain satisfactions, with nearly all domain satisfaction coefficients showing strong significance, particularly financial satisfaction and health satisfaction. In terms of the convergent validity, many studies have shown a moderate to strong correlation between the self-report subjective well-being measure with alternative measures (Pavot, 2013; Pavot et al., 1991; Sandvik et al., 1993). Kahneman et al. (2004) observed a moderate correlation ($r = 0.38$) between life satisfaction and daily "net affect," as assessed using the Day Reconstruction Method. A meta-analysis of 44 independent samples revealed a moderate correlation ($r = 0.42$) between self-reported and informant-reported measures of subjective well-being, encompassing affects, life satisfaction, and happiness — indicating that close friends and family do reasonably well carrying out the life satisfaction evaluation on behalf of someone else (Schneider & Schimmack, 2009).

Despite being a reliable and valid measure, the use of subjective well-being measurements in informing public policy still faces challenges, particularly in capturing the effects of public policy (Diener, 2009, p.95). On the one hand, since subjective well-being is constructed by individuals, its measurement inevitably reflects personality or individual traits (DeNeve & Cooper, 1998). If these traits, which are unaffected by public policy, are decisive in determining subjective well-being, then efforts to enhance subjective well-being through public policy may be largely futile. On the other hand, even if public policies successfully alter people's living circumstances, changes in subjective well-being may not occur due to adaptation and social comparison mechanisms, as discussed in Section 1.2.2.2 (Odermatt & Stutzer, 2017). Although subjective well-being has its limitations, as Diener (2009, p.46) stated, "these limitations are often different from those of economic and social indicators." Therefore, it can serve as a complement, playing a significant role in areas where socio-economic indicators are difficult to apply, such as the valuation of non-market goods (Dolan & White, 2007).

1.3 Study area: geographic and policy context

As Chapters 3 and 4 of this dissertation use the *Clean Heating Policy* in rural Beijing as a case study to evaluate the impacts of energy transition, this section provides a brief introduction to the geographic and policy context to better support the subsequent chapters.

This introduction helps establish the context for interpreting the results in later chapters and assessing the external validity of the findings. For example, these insights may be relevant to other regions in China and even to developing countries with strong heating demand in Eastern Europe and Central Asia (X. Wu et al., 2004). Some contextual information is also provided in the respective chapters.

1.3.1 Geographic context: rural households in Beijing

This section provides a brief overview of rural households in Beijing, the sample area of this dissertation, with a focus on household energy-related characteristics, including demographics, climate, housing, and energy use.

1.3.1.1 Characteristics of rural Beijing

Beijing, the capital and political center of China, is located on the northern edge of the North China Plain at coordinates 39°56'N, 116°20'E. It is governed as a municipality under the direct administration of the central government with 16 districts including two central urban districts, four suburban districts, and ten rural districts (The People's Government of Beijing Municipality, 2024). As of 2023, Beijing had 2.1 million rural households, encompassing a population of 5.4 million, distributed across 3,768 villages in 178 towns. On average, each rural household consisted of 2.6 people, with 2.1 of them being part of the labor force (Beijing Municipal Bureau of Statistics, 2024).

Among the 31 provinces in mainland China, Beijing ranks third in per capita disposable income for rural households. According to Beijing Municipal Bureau of Statistics (2024), in 2023, the per capita disposable income for rural households in Beijing was 37,400 RMB, with wage income accounting for 72% and transfer income — such as government pension subsidies — comprising 13%. More than 70% of rural household income is allocated to consumption expenditures, with housing (e.g., rent, utilities, and fuel), food (including cigarettes and alcohol), and transportation and communication accounting for 23%, 20%, and 9% of per capita disposable income, respectively.

Despite significant improvements in the economic conditions of rural families in Beijing due to socio-economic development, many still face economic challenges associated with aging populations, lower levels of education, and limited livelihood opportunities (J. Chen et al., 2016).

1.3.1.2 Climate conditions of Beijing

Beijing has a warm temperate, semi-humid, semi-arid monsoon climate with four distinct seasons, characterized by hot and humid summers and dry, cold winters (W. Liu et al., 2009). In 2023, the annual average temperature was 14.3°C, with the highest recorded temperature of 41.1°C on June 22 and the lowest of -16.7°C on January 25 (Beijing Municipal Bureau of Statistics, 2024). In rural mountainous areas below 800 meters above sea level, the annual minimum temperature is 2–5°C lower than in the plains.

The long and cold winter in Beijing implies an intensive need for household space heating. The heating season in Beijing typically lasts for approximately 120 days, from November 15th to March 15th of the following year (Ji et al., 2019). Beijing's heating season closely coincides with periods of heavy air pollution (J. Liu et al., 2016). In January 2013, the North China Plain, including Beijing, experienced a record-breaking period of severe and persistent air pollution, with the monthly average $PM_{2.5}$ concentration reaching nearly 160 $\mu g/m^3$ (R. Li et al., 2015). Since then, the recurrence of severe air pollution during nearly every heating season suggests that residential heating is a significant contributor to air pollution in the region (Ebenstein et al., 2017; Q. Zhang et al., 2019).

1.3.1.3 Housing and space heating in rural Beijing households

Rural household dwellings in Beijing share typical characteristics of northern China's rural areas: the vast majority are self-built, single-story brick-and-tile houses constructed in a decentralized manner (Shan et al., 2015). With socio-economic development, the per capita living area of rural households in Beijing has steadily expanded, growing from just 9 m^2 in 1978 to 53 m^2 in 2023 (Beijing Municipal Bureau of Statistics, 2024).

Since most rural dwellings are self-built and lack standardized construction guidelines, their housing envelopes exhibit poor thermal performance (Yang et al., 2010). In rural northern China, solid clay bricks are the primary wall material, with an average wall thickness of only 33 cm (Building Energy Research Centre at Tsinghua University, 2012). Most rural homes use single-glazed windows, and in some economically disadvantaged households, paper-pasted windows or half-paper, half-glass windows are still in use. The roof, a crucial component of the building structure, is typically made of bricks and tiles and often lacks sufficient thickness (J. Xu et al., 2018). In 2016, less than 20% of rural homes in northern China had any insulation, resulting in space heating energy consumption per unit of floor area being at least twice that of urban buildings (National Development and Reform Commission, 2017). Therefore, home insulation renovations are a key measure to reduce building energy consumption and improve heating efficiency in rural homes (Energy Foundation and Building Energy Conversation Research Center of Tsinghua University, 2022).

Solid fuels, particularly mineral coal, are the primary fuel sources for space heating in rural northern China (Mestl et al., 2007). In 2014, before the implementation of the large-scale rural household energy transition intervention, China's rural household coal consumption reached 197 million tonnes, with the northern region accounting for 81% of this total (of Tsinghua University, 2020). That same year, rural households in Beijing consumed approximately 6 million tonnes of coal. Since 90% of rural household coal consumption in Beijing was used for space heating, this means that Beijing's coal consumption for space heating in 2014 was around 5.14 million tonnes (Research group on household energy consumption, 2016). With the implementation of the *Clean Heating Policy*, rural household coal consumption in China and Beijing decreased to 159 million tonnes and 0.7 million tonnes, respectively, by 2018. In addition to coal, biomass fuels play a significant role in China's rural household energy consumption. In 2014, rural households in China consumed 114 million tonnes of firewood and 75 million tonnes of straw for cooking and space heating.

Rural households in northern China use various methods to burn solid fuels for heating. The most common approach is a combination of a traditional coal stove and hot water radiator systems, where the coal stove heats water that circulates through radiators to warm multiple rooms (of Tsinghua University, 2020). Another common method is directly heating a single room using the heat from a traditional coal stove (Y. Zhou et al., 2021). The kang, a hollow brick bed, is also a traditional heating method in rural households. It is typically connected to a wood-burning stove in the adjacent kitchen, allowing hot air to circulate within the brick structure and provide heat (Zhuang et al., 2009).

With economic development, small electric heating devices, such as electric blankets and portable electric heaters, have also become more common in rural households (Research group on household energy consumption, 2016).

1.3.2 Policy context: the *Clean Heating Policy*

The *Clean Heating Policy*, an intervention aimed at reducing and replacing coal used for rural household space heating, is part of a series of energy transition policies introduced by the Chinese government since 2013 to combat severe air pollution. This section provides a brief overview of the key measures and implementation process of the *Clean Heating Policy*.

1.3.2.1 Implementation process

After severe and persistent air pollution in China in January 2013, which not only threatened the health of hundreds of millions of people, but also brought issues such as "Haze," "Air Pollution," and "$PM_{2.5}$" to the forefront of public concern, air quality became a major focus of public and government attention (Gao et al., 2017; M. Li & Zhang, 2014). In September 2013, China's State Council issued the Action Plan for Air Pollution Prevention and Control, describing ten key measures, including "accelerating the adjustment of the energy structure and increasing the supply of clean energy" and "strengthening comprehensive management and reducing the discharge of multiple pollutants." One of the measures explicitly called for gradually replacing coal with natural gas or electricity through subsidies to expand the scope of high-polluting fuel prohibition zones. The plan also set clear air quality targets to be achieved by 2017, such as limiting Beijing's annual average $PM_{2.5}$ concentration to 60 $\mu g/m^3$ (State Council of China, 2013).

Guided by the central government's approach, local governments developed and implemented their own air pollution mitigation action plans for the period 2013–2017. As a key region for air pollution control, the Beijing-Tianjin-Hebei region and its surrounding areas outlined in their action plan a commitment to gradually reducing coal use for cooking and heating in urban, suburban, and rural areas by enhancing the supply of electricity and natural gas as alternative energy sources (Beijing Municipal Ecology and Environment Bureau, 2013). From a regional perspective, the *Clean Heating Policy* has been implemented in phases, beginning with the Beijing-Tianjin-Baoding-Langfang adjacent areas, then expanding to 43 core cities in Beijing-Tianjin-Hebei and surrounding provinces, and eventually extending to 16 provinces across northern China (F. Wang, 2024). According to F. Wang (2024), by the end of 2023, the *Clean Heating Policy* had reached 39 million rural households in northern China, reducing bulk coal consumption by more than 80 million tonnes and synergistically cutting carbon dioxide emissions by nearly 160 million tonnes.

Beijing began adopting clean energy alternatives to coal-fired household heating as early as the early 2000s, initially targeting aging single-story housing communities in central urban areas that were difficult to integrate into the district heating system (S. Zhou, 2020). At that time, the primary technical solution for clean heating was the thermal storage electric heater. Beijing was also one of the first cities to launch pilot projects under the broader *Clean Heating Policy* targeting coal use for heating in suburban and rural households after 2013. The same year the Action Plan for Air Pollution Prevention and Control was released, Beijing initiated a pilot project to replace coal with electricity in 14 villages (Xinhua Net, 2017). In the following years, the *Clean Heating Policy* was rapidly promoted in Beijing's plains. By the end of 2018, Beijing had essentially achieved "coal-free" status in these areas, with a total of 2,963 villages and approximately 1.1 million rural households completing the *Clean Heating Policy* (Beijing Association for Sustainable Development, 2021).

After 2018, the *Clean Heating Policy* began to be implemented in Beijing's mountainous areas. However, due to challenges such as the difficulty of infrastructure renovation in these regions, the implementation progress slowed down. By the end of 2024, Beijing reported that it had completed clean heating in 3,595 villages, achieving a clean heating rate of 96.7% among rural households (Beijing Municiple Bureau of Agriculture and Rural Affairs, 2025).

Compared to other northern provinces, such as Hebei and Shaanxi, which have primarily used natural gas to replace coal for rural household clean heating, about 90% of rural households in Beijing have achieved clean heating through *Coal to Electricity* conversions (Energy Foundation and Building Energy Conversation Research Center of Tsinghua University, 2022). One significant advantage of electricity over natural gas is its relatively stable supply. During the process of replacing coal with electricity in rural areas of Beijing, the selection of heating equipment initially involved direct electric heaters and thermal storage electric heaters during the pilot stage. However, due to challenges such as high costs, inadequate heating performance, and incompatibility with rural living habits, air-source heat pumps were ultimately chosen as the primary technological solution (Xinhua Net, 2017).

Beyond electricity and natural gas, achieving clean heating remains challenging in provinces with extremely cold climates and underdeveloped economies, such as those in the northeast and northwest. As a temporary solution, processed biomass pellets have been introduced as an alternative to coal during the pilot stage in these provinces (Wei et al., 2024).

1.3.2.2 Policy details

The *Clean Heating Policy* primarily consists of two key aspects: prohibiting the use of bulk coal for heating in rural households and promoting clean heating through subsidies.

In our sample area, Beijing, clean heating serves as a means of coal reduction and is actually part of the *Coal Reduction and Substitution* (减煤换煤) policy. Specifically, the use of low-sulfur coal briquettes as a substitute for traditional bulk coal is implemented as a parallel policy alongside clean heating interventions such as *Coal to Electricity* and *Coal to Natural Gas*. By 2017, all villages in Beijing were covered by the *Coal Reduction and*

Substitution policy, meaning that households that had not yet transitioned to clean heating were provided with subsidized low-sulfur coal briquettes by the government. Each autumn, the village committee submits an order for low-sulfur coal briquettes to the government based on household needs for the heating season. The government's partner supplier then delivers the briquettes directly to rural households. Once a village implements the *Clean Heating Policy*, it can no longer request coal briquettes from the government, and households are prohibited from using coal for heating as the supply is cut off.

Once a village is designated by the government as a target for the *Clean Heating Policy*, the State Grid Corporation of China upgrades the village's infrastructure, such as power transmission lines. Afterward, households can choose from several brands of clean heating equipment selected by the village committee.

For air-source heat pumps in *Coal to Electricity*, the subsidy standard is set at 200 RMB/m^2 of heating area, funded by both city and district governments, with a total subsidy cap of 24,000 RMB per household (The People's Governemnt of Beijing Municipality, 2016). Given that the average rural household in Beijing has a house area of approximately 120 m^2, this means that the vast majority of rural households can receive an appropriately sized air-source heat pump at no cost. The full subsidies for air-source heat pumps alleviate the financial burden of high upfront equipment costs during the early stages of the energy transition. Considering that the air-source heat pumps in rural homes that were among the first to transition from coal to electricity have reached the end of their service life, the Beijing municipal government issued an additional subsidy plan in 2024 to support the upgrading of *Coal to Electricity* heating equipment (The People's Governemnt of Beijing Municipality, 2024).

For households in Beijing that transitioned from coal to natural gas, the municipal and district governments each subsidize one-third of the equipment purchase cost, meaning that households may need to cover the remaining one-third themselves (The People's Governemnt of Beijing Municipality, 2016).

To reduce the operating costs of clean heating, Beijing provides multiple layers of subsidies for energy prices. Currently, 70% of Beijing's electricity supply comes from thermal power generation in neighboring provinces such as Hebei, Shanxi, and Inner Mongolia (Beijing Municipal Bureau of Statistics, 2024). Residential electricity for daily use follows a fixed-tier pricing system, where rates increase progressively based on consumption. The first tier, for households consuming less than 240 kWh per month, is priced at 0.488 RMB/kWh (The People's Governemnt of Beijing Municipality, 2025).

For rural households in the *Clean Heating Policy*, during the heating season (November 15th to March 15th of the following year), they benefit from an off-peak electricity rate of 0.3 RMB/kWh from 8 PM to 8 AM the next day. Additionally, both the municipal and district governments provide subsidies of 0.1 RMB/kWh each, with a total subsidized electricity consumption limit of 10,000 kWh per household per heating season (The People's Governemnt of Beijing Municipality, 2016). This means that households effectively pay only about 20% of the regular electricity price for nighttime space heating.

For households that transitioned from coal to natural gas, the government provides a subsidy of 0.38 RMB/m^3 on top of the rural residential heating gas price of 2.61 RMB/m^3. The subsidy is capped at 820 cubic meters per household per heating season.

From 2013 to 2020, the municipal and district governments of Beijing allocated 22 billion RMB in subsidies for clean heating policy equipment, with annual operating subsidies exceeding 1 billion RMB (Beijing Association for Sustainable Development, 2021).

Such a heavy subsidy burden is difficult for surrounding provinces to sustain, resulting in lower subsidies for rural households under the clean heating policy compared to those in Beijing. For example, in some cities in Henan and Hebei provinces that were part of the first batch of *Clean Heating Policy* implementation through *Coal to Electricity* conversions, equipment purchase subsidies covered only 70–85% of the cost. In some cities included in the second batch of implementation, subsidies were even lower, covering only 50% of the cost.

Regarding electricity bill subsidies, the maximum subsidy per heating season ranges from 400 to 2,400 RMB, and in some cities in Henan province, there is no subsidy for operating costs at all. Therefore, when interpreting the external validity of the results presented in the later chapters for other northern Chinese provinces implementing the *Clean Heating Policy*, it is essential to consider the significant differences in subsidy levels between these provinces and Beijing.

1.3.3 Implications for other countries

Despite the high financial costs associated with subsidizing the *Clean Heating Policy*, the policy has significant potential to effectively drive the energy transition, enhance household and regional air quality, and mitigate health risks (Ma et al., 2023; Meng et al., 2023; X. Zhang et al., 2019). Therefore, it serves as a valuable reference for other countries, particularly developing nations that rely on coal for household space heating. In this section, I will provide some context for the external validity of the *Clean Heating Policy* by briefly describing the basic conditions of other developing countries that rely on coal for space heating.

Kerimray et al. (2017) utilized energy balance data from the International Energy Agency to identify the nine countries with the highest per capita residential coal consumption in 2014: Poland, Kazakhstan, Mongolia, Ireland, South Africa, the Czech Republic, China, the Republic of Korea, and Hungary. Despite representing only 21% of the global population, these countries accounted for 86% of the world's residential coal consumption. Most of them are major coal producers and are situated in cold regions, resulting in a significant demand for heating, with South Africa being an exception. Approximately 40–80% of residential coal consumption in these countries is allocated to space heating. Considering data availability and national representativeness, we next provide a brief overview of the climate conditions, space heating practices, energy consumption, and household energy intervention programs in Poland and Mongolia.

Poland is located in Central Europe and is considered to have a temperate "transitional" climate, with an average annual temperature of approximately 7°C (Błaś & Ojrzyńska, 2024). January is typically the coldest month, and the space heating season generally lasts from October to the end of April (Canales et al., 2020; Chwieduk & Chwieduk, 2021). A large number of Polish households rely on solid fuel combustion for space heating, with this proportion reaching as high as 90% in rural areas by 2018 (Frankowski & Herrero, 2021; Księżopolski et al., 2020). In 2013, Polish households consumed 10.77 million Mg of hard coal, accounting for 14% of the country's total hard coal consumption (Pyka & Wierzchowski, 2016). To promote the transition of household heating energy, Poland has implemented various measures. In addition to the broad prohibition of fossil fuels and solid fuels as heat sources under the 2016 Anti-Smog Act, financial subsidies have been introduced through programs such as the "Clean Air" program and "Moje Ciepło (My Heat)" program to support this transition (Kubiczek et al., 2023). These programs provide financial assistance for the purchase and installation of advanced heating systems, including replacing outdated coal stoves in older single-family buildings with compliant boilers and installing ground-source or air-source heat pumps in new buildings (Jagiełło et al., 2022).

Mongolia is a landlocked country in East Asia, bordering northern China. Mongolia has a harsh temperate continental climate with distinct seasons, but its annual average temperature is only 0.7°C (Yembuu, 2021). The coldest month, January, has an average temperature from −15°C to −30°C (Batima et al., 2005). These extreme conditions result in an extended heating season that lasts for eight months, from September 15 to May 15 (Batsumber & He, 2023). Of Mongolia's 3 million population, 45% reside in the capital, Ulaanbaatar, with 60% of them living in the city's ger districts (Erdenedavaa et al., 2018). Nearly all households in ger districts rely on raw coal combustion for space heating, with the city's 160,000 gers consuming an average of 5 tons of coal and 3 cubic meters of wood per year for heating (Allen et al., 2013; Tong et al., 2018).

The extensive use of solid fuels for heating makes Ulaanbaatar one of the most severely air-polluted cities in the world during winter (Amarsaikhan et al., 2014). To address severe air pollution, Mongolia has implemented stove intervention programs for household heating and launched pilot projects promoting the use of modern energy sources for heating. In 2011, the Mongolian government, in collaboration with the U.S. Millennium Challenge

Account, introduced high-efficiency, low-emission improved stoves to 50,000 households in ger districts (Hill et al., 2017). With subsidies, households only paid 7–14% of the original price (Greene et al., 2013). The evaluation report indicates that while the program reduced household heating-related pollutant emissions and households were satisfied with the heating performance, it did not significantly reduce household coal consumption (Greene et al., 2013; Lodoyasamba & Pemberton-Pigott, 2011). A pilot project involving air-source heat pumps in seven households in Ulaanbaatar demonstrated that, even in the world's coldest capital, the heat pump's efficiency was comparable to that observed in poorly insulated rural homes in northern China. The operating costs of heat pumps were similar to those of coal stoves and remained within the household affordability range. However, large-scale implementation faces challenges related to high upfront costs and the reliability of electricity supply (Pillarisetti et al., 2019).

Through the discussion of Poland and Mongolia — two countries located in different regions with distinct political systems and levels of economic development — it becomes clear that air pollution is a common challenge faced by countries relying on household coal heating. This challenge also serves as a key driver for policy interventions in household heating. In terms of intervention pathways and policy approaches, both countries exhibit similarities with China's *Clean Heating Policy* in northern rural areas. For instance, they have adopted low-pollution coal or high-efficiency stoves as transitional solutions, with the ultimate goal of achieving high-efficiency electric heating through technologies such as air-source heat pumps. Therefore, the discussion in this paper on the *Clean Heating Policy* offers important insights for energy transitions in developing countries with significant heating demands, including Poland and Mongolia.

Chapter 2

Rural household energy transition in China: trends and challenges

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Abstract

Against the backdrop of both environmental and health issues caused by inefficient combustion of solid fuels in households, the transition to clean energy is a critical development imperative. This study uses publicly available administrative data spanning nearly 30 years at the provincial level to characterize the "business as usual" (BAU) energy transition in China's rural household sector in order to inform interventions needed to achieve clean energy goals. We first describe the temporal trends and spatial characteristics of energy transitions over the past three decades. We then use a simple two-way fixed effects model to estimate the role that household income growth plays in this transition process. Finally, we predict the timeline for the BAU rural energy transition with an autoregressive integrated moving average (ARIMA) model. Our results show that China's rural household sector has gradually undergone a consistent but geographically uneven transition over the past three decades. Compared with warmer provinces without indoor heating, where a 1,000 RMB increase in per capita income is associated with a 5–10% increase in the share of clean energy, in provinces with heating needs the predicted effect is less than 2%. ARIMA model projections suggest that without policy interventions, for most provinces in northern China the share of clean energy would remain less than 40% by the year 2050. The *Clean Heating Policy* implemented in the North China Plain in 2015 has therefore advanced the energy transition by 10 years in just the 3 years between 2015 and 2018. Together, these results show the potential for interventions in helping spur energy transitions.

2.1 Introduction

Approximately one-third of the world's population relies on solid fuels such as biomass and coal for their basic energy requirements, such as cooking, heating, and lighting (IEA et al., 2022). However, the process of burning these fuels contributes significantly to air pollution and health problems, particularly in low- and middle-income countries (Jeuland et al., 2015; Kim et al., 2011; Rehfuess & World Health Organization, 2006). Household air pollution, a consequence of burning solid fuels, has been linked to acute lower respiratory infections in children, chronic obstructive pulmonary disease, and lung cancer in adults (Rehfuess et al., 2011). In 2019, household air pollution caused over 2.3 million premature deaths, with over 95% of these deaths occurring in low to medium Socio-demographic Index countries (Global Burden of Disease Collaborative Network, 2020). The use of solid fuels also results in time loss for education, rest, and productive activities, particularly for children and women, due to the time spent collecting and preparing biomass fuel (Biswas & Das, 2022; World Health Organization, 2016). Furthermore, energy expenditures often represent a significant portion of low-income households' budgets (Adkins et al., 2012; Alkon et al., 2016; Sánchez-Guevara et al., 2015). For these reasons, Sustainable Development Goal 7 focuses on ensuring that everyone has access to affordable, reliable, sustainable, and modern energy (Villavicencio Calzadilla & Mauger, 2018).

Household solid fuel use presents critical environmental, health, and development challenges. A key measure to address this issue is transitioning from solid fuels (e.g., coal and biomass) to clean energy (e.g., electricity, liquefied petroleum gas (LPG), and natural gas).[1] Various programs have been implemented to promote this transition around the world. In Ecuador, the government has initiated an energy-efficient cooking program, incentivizing 3.5 million households to install and use induction stoves by 2023 (Gould et al., 2018). Nigeria explored a consumer market for ethanol cookstoves, aiming to cover 0.5 million households

[1] In this paper, we define "clean energy" primarily based on whether it contributes to air pollution in households. It is important to note that we do not consider whether the energy used to generate electricity is "clean," such as whether it is generated from coal-fired or renewable sources, as a criterion for defining clean energy.

in Lagos by 2019 (Quinn et al., 2018). In India, the "Pradhan Mantri Ujjwala Yojana Program" distributed 35 million free LPG connections by April 2018 (Dabadge et al., 2018; Kalli et al., 2022). In Bangladesh, the "Solar Home System Program" installed 5.6 million home solar panel systems, providing electricity to about 22 million rural populations, increasing the national electricity penetration rate to 97% in 2020 (Cabraal et al., 2021). China has undergone a series of rural household energy transition programs to improve the energy quality as well as infrastructure development for expanding modern energy accessibility (Carter et al., 2020). Some of the most representative programs are the rural electrification project that has continued since the 1950s and National Improved Stove Program (NISP) since early 1980s (Bie & Lin, 2015; Sinton et al., 2004). By 2016, 100% of China's population had access to electricity (Yang, 2021).

These programs significantly contribute to the energy transition for cooking and lighting, yet China still relies on solid fuels for rural heating (Zheng & Wei, 2019). Over 100 million rural households consumed around 200 million tons of coal for space heating in 2015 (Energy Foundation and Building Energy Conversation Research Center of Tsinghua University, 2022). China's *Clean Heating Policy*, firstly announced in 2013 in Beijing, bans rural households from using coal and subsidizes the transition to electricity and natural gas for clean space heating. By 2021, over 26 million rural households participated in this program (Energy Foundation and Building Energy Conversation Research Center of Tsinghua University, 2022; He & Li, 2020; X. Zhang et al., 2019). As forecasted by T. Ma et al. (2023), the integration of electric cooking and air source heat pumps for heating in rural households by 2060, as part of a carbon-neutral pathway, is anticipated to yield substantial health benefits and positive economic outcomes across the majority of Chinese provinces.

It is widely believed that policies are necessary to accelerate the transition to clean energy globally. But how much time do these policies "save" in the transition process? If the transition relied solely on general social and economic development, how long would it take to occur? The "energy ladder" and "energy stacking" theories propose that households transition from traditional solid fuels to cleaner sources as their socioeconomic status improves

(Hosier & Dowd, 1987; Van der Kroon et al., 2013). Empirical studies indicate that this transition is not always a discrete, one-way shift and that households often continue to use inferior fuels even as they adopt cleaner ones (Carter et al., 2020; Maina et al., 2017; Masera et al., 2000; Wu & Zheng, 2022).

Most studies in China on rural household energy transitions focus on describing energy use in specific administrative areas (e.g., county and province) or comparing differences across areas using cross-sectional survey data (B.-D. Hou et al., 2017; B. Hou et al., 2019; Jiang & O'Neill, 2004; R. Wang & Jiang, 2017; Wu et al., 2017). Several recent studies have also used longitudinal surveys to understand factors related to energy transitions over time (Carter et al., 2020; Liao et al., 2019; C. Ma & Liao, 2018; Tang & Liao, 2014; Tao et al., 2018; Wu & Zheng, 2022; Zhou et al., 2009). For instance, Tao et al. (2018) conducted a nationwide survey in rural China in 2012 that included nearly 35,000 households. Using retrospective self-reported data, they examined the energy mix patterns for cooking and space heating across all Chinese provinces from 1992 to 2012. They found that, compared with the rapid transition for cooking, the energy transition for space heating is slow. Using per capita income, heating demand days, and coal prices at the provincial level, they found that these explanatory variables had a better degree of explanation for the variation in cooking energy transition compared to heating. In their follow-up study using data from a 2017 survey, which encompassed approximately 57,000 rural households spanning all provinces of mainland China, they found that despite a promising decline in the usage of biomass for both cooking (41%) and space heating (59%) purposes compared to levels observed in 2012, coal continued to hold a dominant position in fulfilling space heating needs (Shen et al., 2022). Most of these studies, based on cross-sectional or short-panel field survey data, span less than five years. This time scale limitation from surveys prevents us from understanding the temporal trend of BAU energy transition.

The use of administrative data from statistical offices offers an unparalleled advantage in analyzing national and provincial energy transition trends in this regard. Studies utilizing administrative statistics from the China Energy Statistical Yearbook and China's Rural Energy Yearbook, released by the Ministry of Agriculture, have rigorously analyzed temporal trends on the national or provincial level (Han et al., 2018; X. Wang & Feng, 1997; Yao et al., 2012; M. Zhang & Guo, 2013; X. Zhang et al., 2022; Zhou et al., 2008). For instance, Han et al. (2018) utilized province-level panel data from administrative statistics between 1991 and 2014 to reveal that, during this period, the rural household energy transition in China followed the "fuel stacking" pattern, with traditional commercial energy and advanced commercial energy having weak substitution effects on biomass energy. However, administrative data have been largely overlooked in recent studies in this field.

Several factors contribute to this situation. Firstly, the China Energy Statistical Yearbook, which is the most important administrative data in this field, does not include non-commodity energy (i.e., biomass fuels) quantities. We pursue this issue in the next section. Second, it is commonly understood that these statistics severely underestimate coal usage due to the fragmentation and complexity of rural household purchase sources (Cheng et al., 2017). L. Zhang et al. (2009) detailed the causes of this concern from the perspective of the different statistical methods of commercial and non-commercial energy data. Specifically, non-commercial energy data are typically gathered by the Ministry of Agriculture via its network of offices at the provincial, county, and township levels, while commercial energy data are typically obtained by the National Statistics Bureau through an annual survey of rural households (Li et al., 2019). Nevertheless, the unique advantages of administrative energy statistics include: first, they are the most comprehensive and representative and have the longest time series among available rural household energy data for China; second, they are publicly available; third, and perhaps most importantly, they represent the information that was available to public policy makers designing government intervention.

Our study tackles data concerns regarding incomplete and inconsistency by integrating all publicly available administrative energy statistical data sources. To shed light on rural household energy transition in China, we approach the following research questions: (1) What are the trends and characteristics of rural household energy transition on national and provincial levels in past decades in China? (2) How would a clean energy transition progress based on general economic growth without interventions? (3) What is the timeline for provinces in different energy use zones to achieve energy transition, and how much can interventions (like the *Clean Heating Policy*) accelerate this process? By examining these questions, we aim to provide insights into the past trends, current state, and future prospects of China's rural household energy transition, as well as the potential impact of intervention programs.

Our study contributes to the existing literature on rural household energy use in China in the following ways: First, we provide a comprehensive integration of administrative statistics. By combining all publicly available administrative statistics on rural household energy data in China, we offer an extensive description of past trends in the field. Second, we present circumstantial evidence of the discrepancies between energy transitions in cooking and heating within the framework of the Chinese rural domestic energy use zone. Third, employing a time-series approach, we forecast the timeline of the energy transition, emphasizing the necessity and timeliness of interventions such as the *Clean Heating Policy*.

2.2 Data and methods

2.2.1 Data

Our analysis is based on provincial-level rural energy statistics in China from 1991 to 2018, focusing on data sources that include rural household energy use, population, and per capita income. By "rural household energy use," we refer in this paper to the quantities of biomass fuels (e.g., firewood, straw, and biogas), coal, electricity, and commercial gas fuels (e.g., LPG and natural gas) used by rural households for ends such as cooking, space heating and cooling, lighting, and entertaining. Other energy sources that have not been widely used in rural China, such as dung and solar, are not included in this study.[2]

[2]According to data from the third-round China Agricultural Census (CAC), the proportion of rural households utilizing solar energy as their primary energy source was only 0.2% in 2016, while the usage of other sources (including yak dung) stood at 0.5%. Tibet exhibited the highest utilization rates for these energy sources (solar: 1.2%, other: 48.3%), but we were unable to include it in the main analysis due to data availability constraints (refer to the footnote in the Data section below).

Our primary energy use data are from the China Energy Statistical Yearbook (CESY). It reports the energy use based on a top-down statistical method that starts with a high-level estimate of the total energy consumption of each energy type and then breaks it down into specific provinces and sectors. CESY focuses on commercially provided energy.[3] Existing studies note that biomass fuels, which are usually sourced locally by rural households, are often ignored or severely underestimated in the CESY. And while CESY data includes province-level rural household biomass fuel data based on a bottom-up[4] statistical method from the China Rural Statistics Report (CRSR, published by the Chinese Ministry of Agriculture between 1991 and 2007 and missing values for 1992–1994 and 1997), neither CESY nor CRSR have published province-level biomass fuel data past 2008. This has left a considerable gap in data coverage. To reflect the most current fuel use, we adopted datasets from two research reports: the China Building and Energy Saving Annual Report (CBESAR) for 2014 and 2018 (Building Energy Conversation Research Center, 2016, 2020) and the Typical Rural Energy Model (TREM) for 2015, published by Ministry of Agriculture and Rural Affairs as the supplement to the administrative data (Station of Agricultural Ecology and Resource Conservation, 2019).

We adopted different data strategies for the nation- and province-level analysis for our distinct research purposes. Our nation-level analysis emphasizes the temporal variation of various energy uses. We keep energy types consistent across years from the same data source. That is, the commercial energy data used for nation-level analysis, as well as the biomass fuel data up to 2008, are all obtained from CESY. As for the province-level analysis, the key indicator is the share of clean energy in total energy consumption. To guarantee the comparability of energy types for a province in a year, we adopted the data for a year of each province from the same source. Since the CESY has missing provincial data for several years prior to 2000, our data prior to 2000 for province-level analysis are uniformly derived from CRSR. The data after 2008 are from CBESAR and TREM. To further discuss

[3]By "commercial energy," we refer in this paper to the energy that rural households purchase from the market, which includes coal, electricity, and commercial gas fuels.

[4]The county agricultural bureaus collect data from rural households using field measurements and sample surveys, which are then reported to higher levels of agricultural administrative units in a cascading manner.

energy transition from the perspective of energy structure change, we include the number of rural households that rely on different fuels as their main domestic fuel source in each province from the first (1996) and third (2016) rounds of the China Agricultural Census (CAC) (National Bureau of Statistics of China, 1996, 2016b).[5] The original data from CESY, CRSR, CBESAR, and TREM can be found in hard copies.[6] We manually entered these raw data to form a database for analysis. Table 2.1 shows the data sources used in the analysis to follow.

Table 2.1: Data source of nation-level and province-level analysis. Due to the data constrains, Tibet, Hongkong, Macau, and Taiwan do not within the scope of this study.

Year	Nation-level Analysis	Province-level Analysis
1991–1999	CESY	CRSR
2000–2007	CESY	CESY
2014 & 2018	CESY (commercial energy), CBESAR (biomass fuels)	CBESAR
2015	CESY (commercial energy), TERM (biomass fuels)	TERM

The province-level rural population and per capita income for each year are obtained from the webpage of the National Bureau of Statistics (National Bureau of Statistics of China, 2024).

To better contextualize our analysis, we situate our province-level analysis within the framework of China's rural domestic energy use zones. This zoning approach considers various factors such as climatic conditions, resource endowments, living habits, and socio-economic development levels, and groups the 31 provinces/municipalities of mainland China into seven distinct energy use zones, as indicated by the different colors in Figure 2.1. Provinces within the same zone exhibit similar rural energy usage patterns, whereas there is significant variability across zones. One notable fact about household energy use in rural China is that households in extreme cold and cold zone provinces tend to consume more

[5]The digital version of the first round CAC data can be found on website of China Statistics Bureau (1996). Currently, the third round of CAC data are only available in the hard copy version.

[6]China's economic and social big data research platform provides a digital version of the CESY and CRSR (China's economic and social big data research platform, 2024).

energy for space heating during the winter months, which generally span from November to April the following year. Additional detail on energy use zones differences in area, population, climate, and biomass resource use can be found in Appendix A.1.

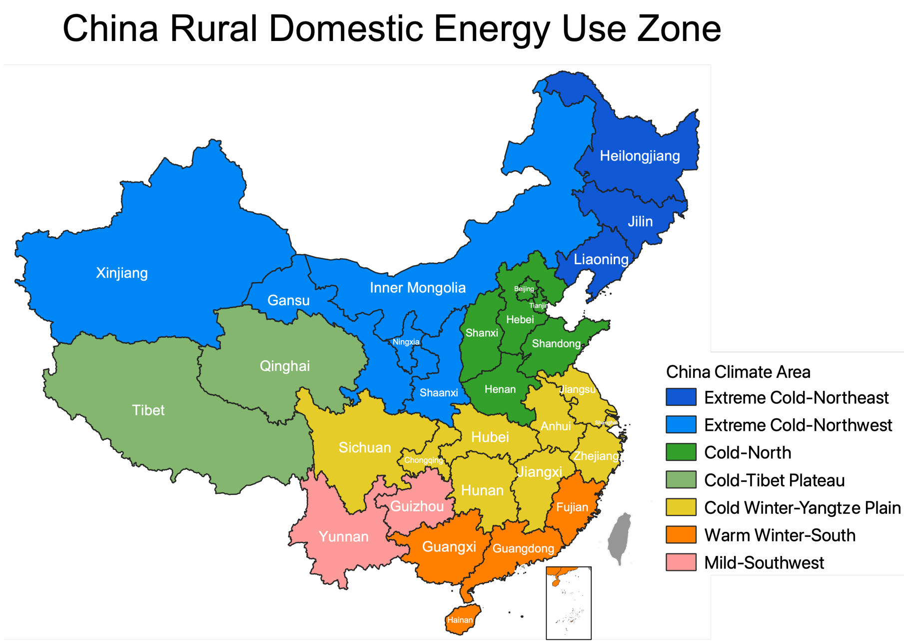


Figure 2.1: Seven rural domestic energy use zones in mainland China. The zoning method uses a layer overlay approach by integrating China's Agricultural Climate Zoning, Building Climate Planning, China Rural Energy Comprehensive Zoning, and Rural Renewable Energy Zoning. In the extremely cold zones, the average temperature is usually below $-10°C$ in the coldest month, and there are generally more than 145 days with a daily average temperature below 5°C; in the cold zones, the average temperature in the coldest month is between 0 and 10°C and days with a daily average temperature below 5°C is generally between 90 and 145 days.

2.2.2 Methods

To examine the temporal trends and characteristics of the BAU energy transition among rural households in China, we begin by exploring the relationship between rising per capita income and the share of clean energy used by rural households (as a proportion of their total energy consumption) through a two-way fixed effects model. Following this, we employ an Autoregressive Integrated Moving Average Model (ARIMA) to forecast the future trend of

BAU energy transition in rural China until 2050, based on historical trends, without any additional interventions imposed.

2.2.2.1 Two-way fixed effects model

The majority of studies in this area use a discrete choice model (e.g., binary logit or multinomial probit model) to discuss factors related to rural household energy choice based on household-level survey data (Paudel et al., 2018; Takama et al., 2012; Wu & Zheng, 2022). Studies based on macro data have used stepwise multiple linear regression (Tao et al., 2018), double-hurdle (Shen et al., 2022), logarithmic mean Divisia index (M. Zhang & Guo, 2013), dynamic panel data (Han et al., 2018), and vector error correction models (Hao et al., 2018) to explore the factors related to rural energy consumption and transition. We use a two-way fixed effects model to estimate the correlation of per capita income growth on the BAU energy transition of provinces in the different energy use zones. The two-way fixed effects model has commonly been used for causal inference with panel data (Imai & Kim, 2021). Here we use a simple two-way fixed effects model to address bias caused by possible unit- and time-invariant unobservable factors. We include two fixed effects terms for province and year. Equation 2.1 shows the two-way fixed effects model we use in this study:

$$\text{Share}_{i,t,z} = \beta_z \text{Income}_{i,t,z} + \text{Province}_{i,z} + \text{Year}_t + \epsilon_{i,t,z} \tag{2.1}$$

where the dependent variable $\text{Share}_{i,t,z}$ is the percentage of clean energy in total rural domestic energy consumption for province i in energy use zone z and year t, the independent variable $\text{Income}_{i,t,z}$ is the rural per capita income for province i in energy use zone z and year t (unit: 1,000 RMB), $\text{Province}_{i,z}$ is the fixed effect term for province i in energy use zone z, $Year_t$ is the fixed effect term for year t, and $\epsilon_{i,t,z}$ is the error term. The coefficient β_z represents the share of clean energy changes associated with a 1,000 RMB increase in rural per capita income for energy use zone z. The coefficient β_z is calculated using the within estimation. We conduct this regression analysis separately for each domestic energy use zone.

$\text{Share}_{i,t,z}$[7] is the clean energy fraction, defined in Equation 2.2:

$$\text{Share}_{i,t,z} = \frac{C_{\text{clean}}}{C_{\text{total}}} = \frac{C_{\text{gas}} + C_{\text{elec}}}{C_{\text{coal}} + C_{\text{biomass}} + C_{\text{gas}} + C_{\text{elec}}} \tag{2.2}$$

where the C_{clean}, C_{total}, C_{gas}, C_{elec}, C_{coal}, C_{biomass} represents the consumption of clean energy, total energy, gas fuels, electricity, coal products, and biomass fuels, respectively.

2.2.2.2 Autoregressive integrated moving average (ARIMA) model

Examining the historical association between income and the BAU shift towards energy sources prior to any policy intervention allows us to predict how an energy transition would have played out in the absence of such a policy. Predicting the trajectory of the BAU transitions provides a counterfactual scenario by which we can judge the effectiveness of attempts to accelerate the process. Among methods for developing such predictions, three commonly employed methods are regression-based formulation, artificial neural networks, and time series models (Kuster et al., 2017). In particular, time series models (e.g., ARIMA) perform well for medium and long-term predictions (Q. Wang et al., 2018).

We use an ARIMA model to predict the BAU rural household energy transition for provinces in different energy use zones in the future. One advantage of ARIMA is that it only requires the past values of the predicted variable itself (share of clean energy in this study), without resorting to exogenous variables (e.g., indicators such as economic development and energy prices) to carry out prediction (Q. Wang et al., 2018). An ARIMA(p, d, q) model incorporates differencing, autoregression, and moving average models as shown in Equation 2.3:

$$y'_t = c + \phi_1 y'_{t-1} + \cdots + \phi_p y'_{t-p} + \theta_1 \epsilon_{t-1} + \cdots + \theta_q \epsilon_{t-q} + \epsilon_t \tag{2.3}$$

[7] All energy consumption in Equation 2.2 and are converted to their coal equivalent; detailed estimates are provided in Appendix A.2.

In Equation 2.3, y'_t on the left side is the differenced series which is the change between consecutive observations in the original series. Differencing helps stabilize the mean of a time series. The degree of differencing (d) specifies the number of times the data have been differenced in the ARIMA(p, d, q) model. For example, in an ARIMA$(p, 1, q)$ model where $d = 1$, $y'_t = y_t - y_{t-1}$; in an ARIMA$(p, 2, q)$ model where $d = 2$, $y'_t = (y_t - y_{t-1}) - (y_{t-1} - y_{t-2})$. In practice, it is almost never necessary to go beyond second-order differences ($d \leq 2$) (Hyndman & Athanasopoulos, 2018).

The "predictors" on the right side include both lagged values of y_t and lagged errors. The autoregression model ($\phi_1 y'_{t-1} + \cdots + \phi_p y'_{t-p}$) predicts the future energy transition based on the lagged values of clean energy share. The order p in the ARIMA(p, d, q) model indicates that the lagged values (y_t) of the previous p years are included in the autoregression model. The moving average model ($\theta_1 \epsilon_{t-1} + \cdots + \theta_q \epsilon_{t-q}$) predicts based on the lagged forecast errors in a regression-like model. The order q in the ARIMA(p, d, q) model indicates that the lagged forecast errors of q previous years are included in the moving average model. c is the mean value of the time-series data and ϵ_t is the error term.

Different choices of the parameters (i.e., p, d, q) in the ARIMA(p, d, q) model represent different possible models. We use the "auto.arima" function in the R "forecast" package (Hyndman & Khandakar, 2008; Hyndman et al., 2018), which determines the optimal parameters (p, d, q) combining unit root tests, minimization of Corrected Akaike's Information Criterion (AICc) and Maximum Likelihood Estimation (MLE) after going through different parameter combinations. See the Table A.4 in the Appendix for details on ARIMA parameters for different energy use zones.

To prepare the data for ARIMA analysis, we addressed missing values in the share of clean energy for each domestic energy use zone between 1994, 1997, and 2008–2014, which are 14 missing values for Cold-Tibet Plateau zone (C-T) and 10 missing values for other zones, using linear interpolation to replace missing values with the "imputeTS" package in R (Moritz & Bartz-Beielstein, 2017).

2.3 Results and Discussion

2.3.1 National level rural household energy transition in China between 1991 and 2018

We begin by examining the historical trends in China's rural domestic energy sector over the past 30 years at the national level, as shown in Figure 2.2. In terms of energy consumption, to prevent optimistic estimates of energy derived from the decrease in total solid fuels due to rural depopulation accompanying urbanization, we have selected per capita consumption as an indicator. Concurrently, this metric can capture shifts in the energy mix within households, thereby offering insights into the health impacts of indoor air pollution. Figure 2.2(a) indicates a continuous increase in per capita energy consumption, reaching 600 kg coal equivalent (kgce) in 2018, which is twice the amount consumed in 1996. The different colors in the plot represent various energy sources and reflect the changes in the energy structure. Notably, commercial energy (i.e., coal, electricity, LPG, and natural gas) consumption has consistently risen over the past two decades, particularly clean energy (i.e., electricity, LPG, and natural gas). Of these, electricity consumption has grown the fastest, reaching 325 kgce per capita in 2018, which is twenty times the amount consumed in 1996. Electricity has become the dominant source of domestic energy consumption, accounting for more than 50% of total energy consumption in 2018.

While gas consumption has increased tenfold in 20 years, it only accounts for about 5% of energy consumption. LPG remains the most widely used gas fuel in rural China due to its efficiency, ease of transport, and affordability. Other gas fuel types, such as natural gas and biogas, are not as popular due to resource shortages and transmission constraints (Economides & Wang, 2010). Over the past 20 years, while commercial energy consumption has been growing rapidly, the share of coal in China's rural domestic energy mix has remained low at around 15%. This is primarily because household coal consumption is concentrated in a few provinces in North China and is mainly used for space heating (Wu et al., 2019).

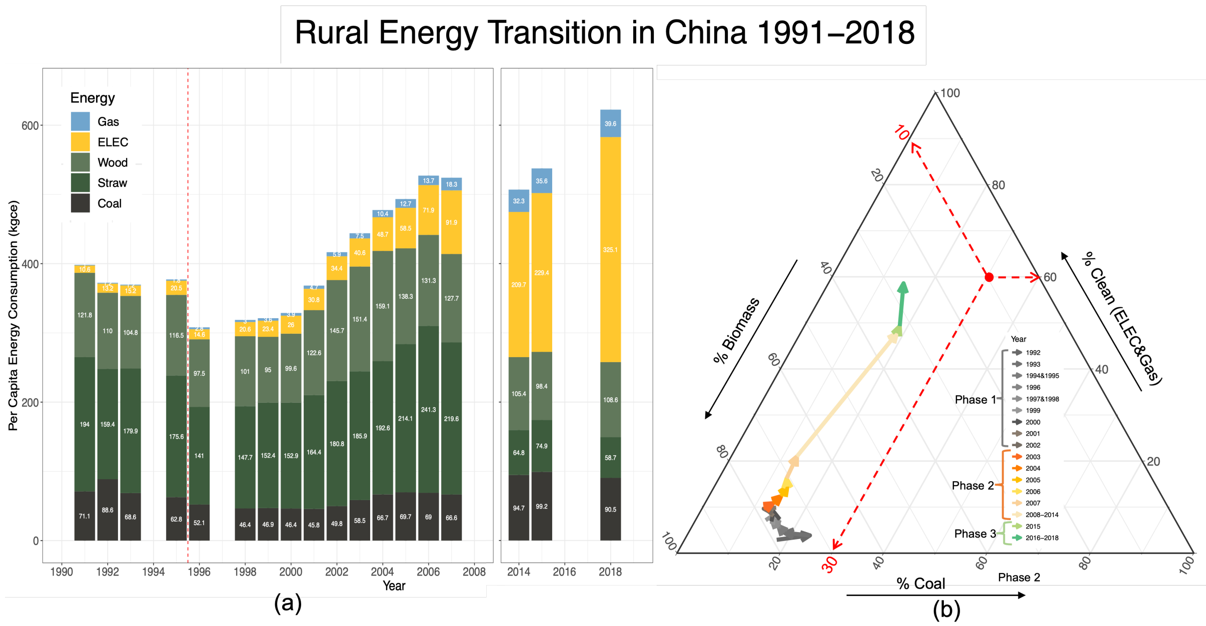


Figure 2.2: Rural household energy transition in China 1991–2018. Each arrow in Figure 2.2(b) represents the change in these three dimensions (i.e., Biomass, Coal, and Clean) over a specific timeframe (usually one to several years, based on data availability). These arrows depict the starting and ending points, with the former showing the share of each energy type in total consumption at the period's beginning and the latter indicating the share at the end. The employed color scheme further categorizes these changes into three identified transition phases: Phase 1 (gray), Phase 2 (orange), and Phase 3 (green). The red dot and red dashed lines are to guide interpretation, i.e., to obtain the proportions of Biomass, Coal, and Clean corresponding to any given arrow. For instance, the red dot in the figure represents the proportion of Biomass, Coal, and Clean for 10%, 30%, and 60%, respectively.

Contrary to the rapid growth of commercial energy in the last two decades, the per capita consumption of biomass fuels has continued to decline. The consumption of firewood and straw was 122 and 194 kgce in 1991; their consumption reduced to 109 and 59 kgce in 2018, respectively. The decline in the consumption of biomass fuels is mainly due to the substantial decrease in straw. In contrast, the absolute value of per capita firewood consumption has remained stable for thirty years. The share of biomass fuels in per capita energy consumption has dropped from over 80% in the 1990s to only about 25%.

The ternary plot (Figure 2.2(b)) reflects the evolution of China's rural energy mix over the last three decades. The arrows indicate the direction of the transition, which has moved from solid fuels (coal and biomass fuels) to cleaner energy (gas and electricity). The colors of the arrows represent the three phases of the rural household energy transition from 1991 to 2018. We see that an early period, which we call Phase 1 (1991–2002), saw a slow transition with almost no change in biomass (−1%), a minor decrease in coal (−6%), and slight increases in clean energy (+7%). Clean energy only contributed around 10% to rural domestic energy consumption during this period. Phase 2 (2003–2015) was a "commercial transition" period, with biomass fuels decreasing by 44% and a rapid increase in commercial energy. The popularity of clean energy, specifically electricity, drove this transition. The share of coal in the rural domestic energy mix only increased by about 8% during this period. Phase 3 (2015–2018) was a "clean transition" period. Around 2012, the Chinese government turned more attention to combating air pollution, specifically $PM_{2.5}$ pollution, leading to a number of energy transition programs for rural households that began in 2015. These programs, such as the "coal to electricity" and "coal to natural gas" projects in the North China Plain and the Fenwei Plain, were localized but had a national impact. In only three years, the share of biomass fuels and coal reduced by 10% and 5%, respectively.

The figure also shows the acceleration of the energy transition rate in China's rural household sector. From 1991 to 2015, with no significant intervention project, the transition to clean energy progressed by only 5% in the first decade and about 40% in the second decade. The question now is whether this trend will continue at a sustained and rapid pace or encounter bottlenecks, which we will explore in the following sections.

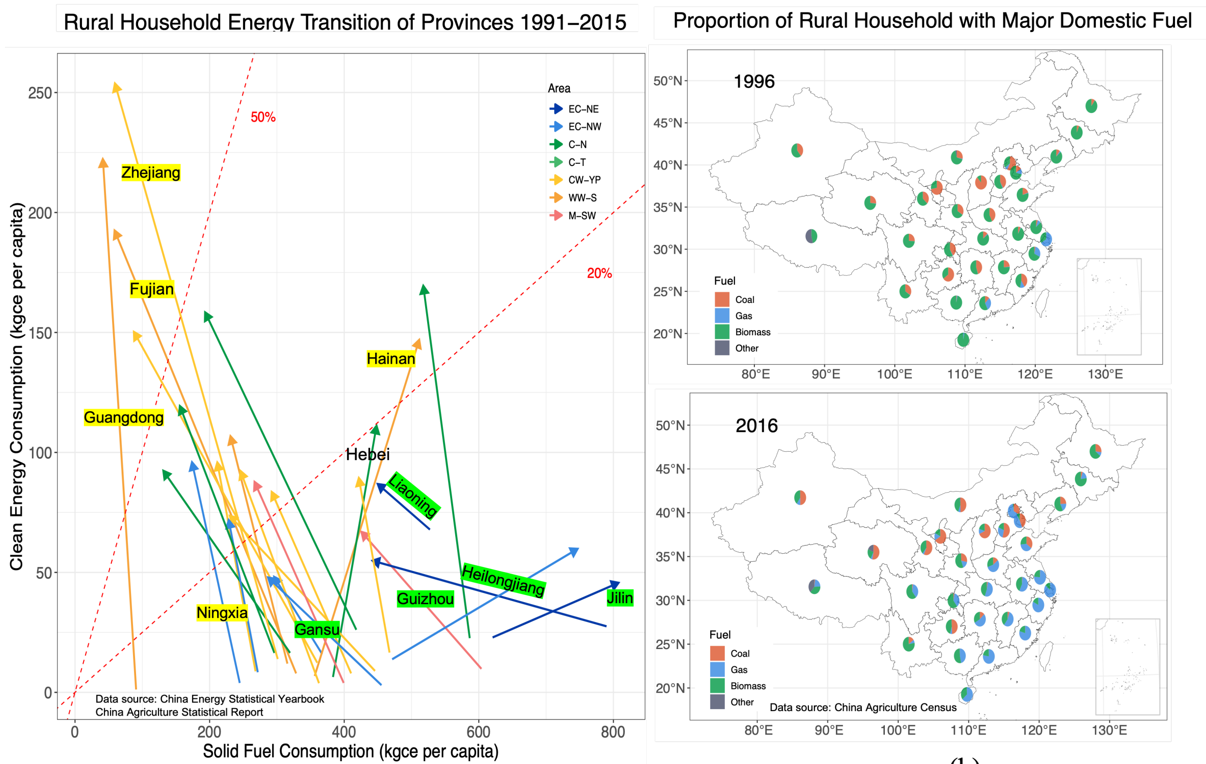
2.3.2 Provincial level rural household energy transition in China

In the previous section, we discussed the temporal trends in the energy transition of rural households at the national level. This section investigates geographic differences in that overall picture.

Figure 2.3(a) illustrates the energy transition at the province level located in different energy use zones from 1991 to 2015. The two red dotted lines in the figure provide a reference for the degree of energy transition. At the base of the arrows, representing the year 1991, there are significant differences between provinces in per capita total energy consumption. For instance, provinces in the Extreme Cold-Northeast zone (EC-NE) have a per capita consumption of solid fuels that is over 500 kgce, approximately double that of provinces in other zones, while per capita clean energy consumption is less than 50 kgce in almost all provinces. Between 1991 and 2015, most provinces witnessed an increase in per capita energy consumption accompanied by a decrease in solid fuel consumption, as indicated by the heads of the arrows. Per capita consumption of solid fuels only increased in four provinces in 2015, namely Heilongjiang, Jilin, Hainan, and Hebei, with two provinces in the EC-NE showing significantly larger increases.

Per capita clean energy consumption increased in all provinces compared with 1991, particularly in the Cold Winter-Yangtze Plain zone (CW-YP) and Warm Winter-South zones (WW-S), where clean energy consumption per capita exceeded 200 kgce in Zhejiang and Guangdong in 2015. In 1991, the share of clean energy in rural domestic energy consumption was far below 20% in all provinces. However, compared with 1991, this share increased in all provinces, especially for provinces in CW-YP and WW-S, where it exceeded 50%. In contrast, the share of clean energy is still lower than 20% for all provinces in EC-NE and most in EC-NW in 2015.

The extent to which the share of clean energy has increased varies greatly across different regions, as indicated by the positions of the arrow ends in Figure 2.3(a). The provinces with the highest and lowest transition degrees between 1991 and 2015 are highlighted with yellow and green text labels, respectively. Notably, the four provinces (Zhejiang, Fujian, Guangdong, and Hainan) with the highest transition degree are located in the CW-YP and WW-S zones, while the four provinces (Jilin, Heilongjiang, Liaoning, and Gansu) with the lowest degree are situated in the Extreme Cold zones, where intense winter space heating demands limit energy transition. Consequently, the clean energy transition on a national level has been primarily driven by the progress in WW-S and CW-YP provinces, while the transition in EC-NE and EC-NW provinces has remained largely stagnant for decades.



(a) (b)

Figure 2.3: Province-level rural household energy transition 1991–2015. Each arrow in Figure 2.3(a) only represents the situation in 1991 and 2015, respectively. The arrows do not indicate any intermediate years between 1991 and 2015. The pie charts within Figure 2.3(b) show the share of rural households' main source of domestic fuels, which is obtained by dividing the number of households by their primary source of domestic fuel by the total number of registered households in each province. "Other" in Figure 2.3(b) is the proportion of households using solar energy and yak dung, etc., as their main source of domestic energy source. All proportions were calculated based on the household number after removing households who reported electricity as their primary source.

We use two maps, shown as Figure 2.3(b), to further show the energy transition in major household fuel at the provincial level. These two maps are based on CAC data.[8] The upper figure in Figure 2.3(b) shows that biomass fuel was the dominant fuel for rural households

[8]To keep the consistency of these two rounds of data, we did not include the number of households that use electricity as their major energy source since that was only reported in 2016 data.

in most provinces in 1996, especially for provinces in EC-NE and WW-S. For Hainan and Guangxi in WW-S, over 95% of rural households took biomass as their primary domestic fuel in 1996. Only in a few provinces, over 50% of households took coal as the primary domestic fuel like Shanxi, Ningxia, and Guizhou, which have rich coal resources. A particular case is Shanghai, which has few rural residents and higher socioeconomic status on average; about 66% of its rural households used gas fuel as their primary domestic fuel even in 1996. The bottom figure in Figure 2.3(b) shows the share of rural households relying on different domestic fuels for provinces in 2016. The primary domestic fuel of each province has changed considerably; meanwhile, this change varies geographically. Gas fuel has been the primary domestic fuel for most rural households in southeastern provinces in WW-S and CW-YP. In a few WW-S and CW-YP provinces in southwestern China, like Chongqing and Yunnan, even though over half of rural households still use biomass as their major domestic fuel, the proportion of households that mainly use gas fuels has reached almost 40%. There is also a greater share of households that use gas fuels as their primary fuel in EC-NW and Cold-North zone (C-N) provinces; the share of rural households that use coal as their major fuel also increases significantly in these provinces. Compared with 1996, coal replaced biomass as the most common fuel in EC-NW provinces except Shaanxi in 2016. As we previously discussed, the pace of energy transition in EC-NE provinces is slow. The share of rural households that take solid fuel gas as primary fuel is still 82%, 83%, and 92% in provinces Liaoning, Jilin, and Heilongjiang, respectively. A notable observation is the prevalence of electricity as a primary energy source among rural households, a factor not included in our analysis due to data consistency concerns. According to the third-round CAC data, 59% of rural Chinese households rely on electricity as one of their primary domestic energy sources in 2016, with usage rates varying from 3% in Xinjiang to as high as 88% in Guizhou.[9]

This section delved into the energy transition of rural households at the provincial level, examining both the quantity and structure of the transition. The significant regional disparities between provinces with and without heating demand suggest a higher dependence on

[9]Please refer to Figure A.1 in the appendix, the map illustrating the complete third-round census data on the "proportion of rural households with primary domestic energy sources," including electricity.

solid fuels for heating compared to cooking. As a result, the shift towards clean energy in C and EC zones poses greater challenges. Moreover, these regional disparities also foreshadow potential bottlenecks in the nationwide energy transition, as provinces in the EC and C zones may stall after the warmer provinces have completed their transitions.

2.3.3 Role of income in the rural household BAU energy transition

Apart from the climatic conditions and corresponding energy needs mentioned above, household income is widely recognized as a critical determinant of the energy transition, clean energy adoption, and suspension of solid fuel use in existing studies (Guta et al., 2022; Lewis & Pattanayak, 2012). With more advanced fuels offering benefits such as time-saving, better living conditions, and improved health, households gravitate toward improved fuels once increased income expands their choice set on energy sources. In this section, we examine the relationship between per capita income and rural household energy transition in different domestic energy use zones. Our analysis provides insights into whether we can expect a BAU energy transition in the near future, given the historically high income growth rate of around 10% per year in rural China.

Figure 2.4 summarizes the regression results from the two-way fixed effect model estimating the role of per capita income in rural household energy transition. As shown in Figure 2.4, per capita income generally plays a more critical role in rural household energy transition for provinces without space heating needs in winter, especially for M-SW and WW-S provinces. Every 1,000 RMB increase in per capita income is associated with about 11% and 5% increase in the share of clean energy in M-SW and WW-S provinces, respectively. The greater effect size of these coefficients suggests an optimistic scenario of BAU transition in provinces in these two zones. However, it seems relying on income growth to achieve BAU energy transition would present a bleak prospect for provinces with space heating needs. In these provinces yearly low temperatures between $-20°C$ and $-10°C$ and moderate heating demands (C-N and C-T), a per capita income increase of 1,000 RMB is only correlated with a modest increase of 0.60–0.77% in clean energy share. In EC provinces with lowest temperatures below $-20°C$ and intensive heating demands, the magnitude of correlation further decreases to approximately zero or even negative. The negative confidence interval for EC-NE can be attributed to the significant heating demand and the traditional heating method of burning solid fuels, such as the kang, in this zone. As income increases, households tend to use more solid fuels to achieve better heating effects. As a result, the proportion of clean energy decreases with rising income, as solid fuel consumption increases faster than that of clean energy. In other words, within the income range covered in this study, the income effect on solid fuel demand is greater than the substitution effect towards clean energy.

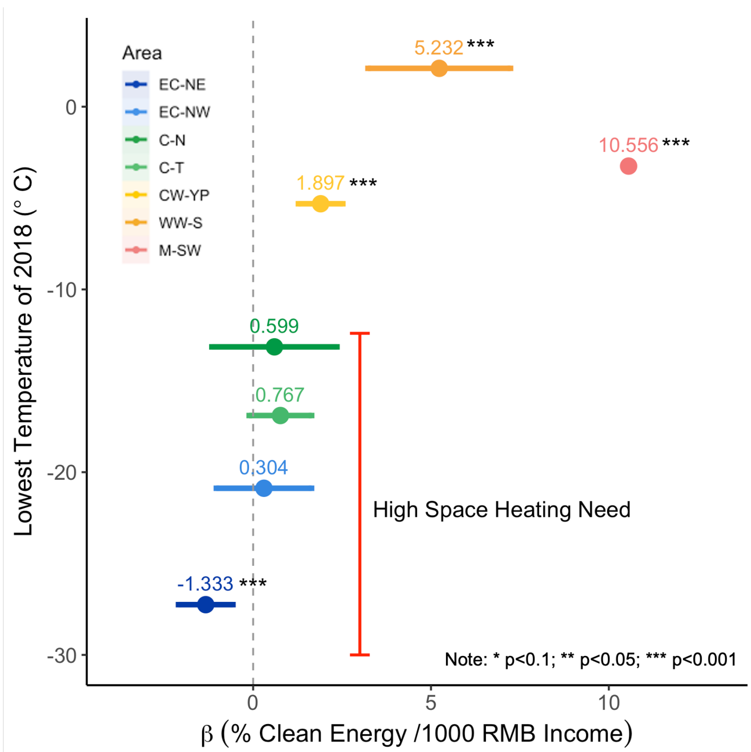


Figure 2.4: Coefficients and confidence intervals of two-way fixed effects model. The sample used in this study is an unbalanced panel of provinces. To report our findings, we have listed the estimations of coefficients and 95% confidence intervals in descending order of the winter 2018 minimum temperatures in each domestic energy use zone. The confidence intervals are based on robust standard errors. We detail the regression results in Appendix A.3.

It is worth noting that in most regression models we analyzed, the R^2 value is less than 0.1, indicating that per capita income explains only a minor portion of the BAU energy transition in most provinces. Considering the time-sensitive nature of policy objectives and the current low share of clean energy, the small coefficients in zones with space heating needs suggest that intervention programs will be necessary to accelerate the transition in those provinces.

2.3.4 Timelines of BAU energy transition

In the previous section, we discussed the role of per capita income growth in the rural household BAU energy transition. Based on our results, it appears to be hard for provinces with space heating needs in rural areas to achieve energy transition solely relying on income growth. The Chinese government has set up a series of environmental and climatic targets to "reach carbon peak in 2030, globally reach the air quality target in 2035, and achieve carbon neutrality in 2060" (Shi et al., 2021). Nevertheless, trajectory the advancement of the social economy and the widespread adoption of commercial energy sources, China's rural residential coal consumption surged from 69 million tons in 1985 to 73 million tons in 2015 (National Bureau of Statistics of China, 2016a; Zhao et al., 2022). This poses a serious challenge to the achievement of carbon emissions and air quality objectives. Therefore, achieving a rural household energy transition, especially a reduction in total coal consumption, in a shorter period is necessary. As a final way to set up a counterfactual of a world in which no policies were enacted, we predict the timeline for transition in different energy use zones based on their historical pre-policy implementation trends.

Figure 2.5 shows the predicted energy transition for different energy use zones from 2018 (2014 for C-N) to 2050, using predictions from the ARIMA models based on historical trends beginning in the early 1990s. The dotted lines and shaded areas in the figure represent the BAU scenario, which indicates the share of clean energy without intervention. As our previous findings suggest, provinces in WW-S, CW-YP, and M-SW which do not require intensive space heating would have expected to complete a full energy transition earlier. According to the prediction results, provinces in CW-YP and WW-S regions would have achieved complete energy transition in rural households before 2050. Even under the conservative estimates of the 95% confidence interval, the share of clean energy in these two areas would have reached about 80%. Although energy transition in M-SW provinces would have occurred a bit later, it has shown a fast pace in recent years, which may have put it on a path toward an estimated share of clean energy of around 80% in 2050. In optimistic estimates, all provinces without intensive space heating demands are likely to complete rural household energy transition.

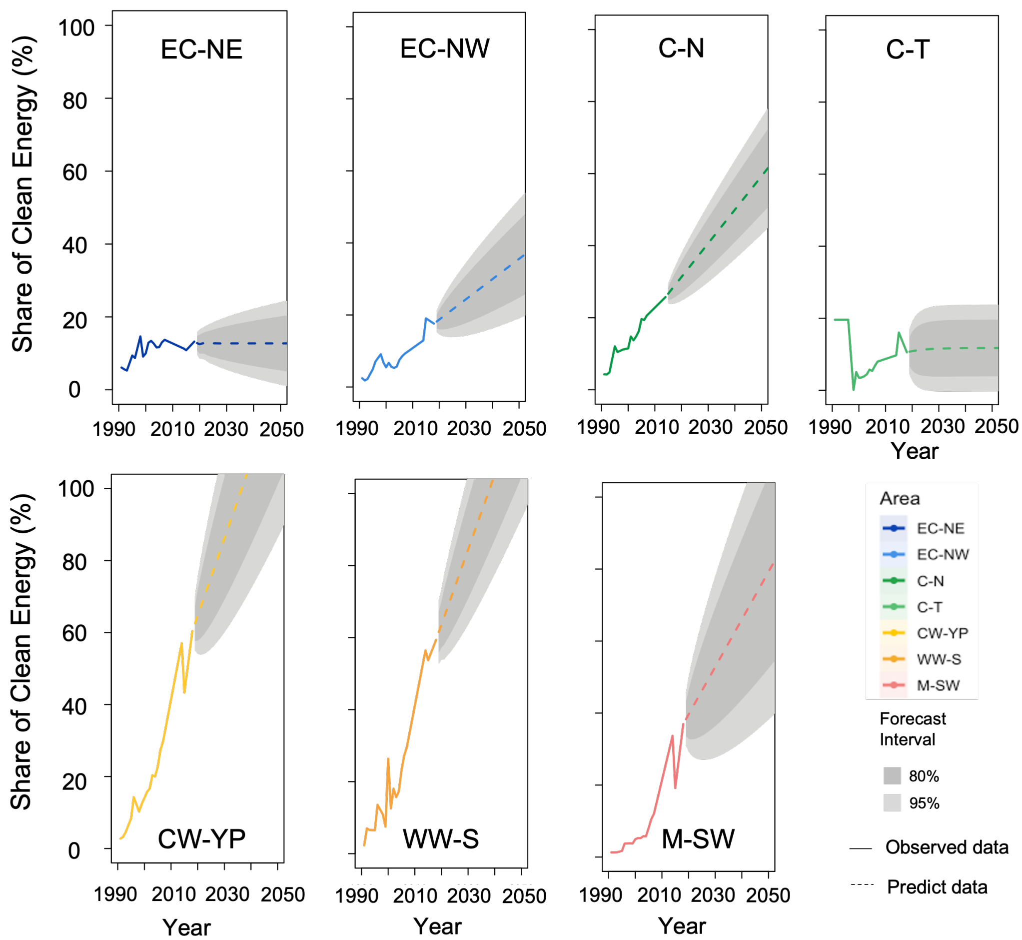


Figure 2.5: Predicted timeline of BAU rural energy transition. The ARIMA(p, d, q) model predicts rural household energy transitions separately for different domestic use zones in the coming decades, using different parameters. The flat dotted lines in EC-NE and C-T indicate that no significant temporal patterns were identified in these regions.

However, for provinces in EC and C zones that require intensive space heating, only those in C-N would have been expected to make measurable progress in the coming decades, perhaps approaching around 70% by 2050. This may be attributed to several factors, including mild space heating needs compared to other EC and C-T provinces, households being more affluent, and administrative pressure caused by severe air pollution in the area (which spurred several small-scale energy interventions in the recent decade like the "Sending LPG to Villages (送气下乡)" program in Beijing). The transition to clean energy in rural households across the EC provinces, especially EC-NE, would have been prolonged into the coming decades. Even under an optimistic scenario, the proportion of clean energy in the EC-NE areas is forecasted to remain below 20% by 2050 (at the high end of 95% confidence interval). Unfortunately, the provinces in C-T have the least favorable outlook. Limited infrastructure and unfavorable topography make it challenging to transport clean energy to the region, while low incomes make it difficult for households to afford advanced clean energy. These factors are slowing down the pace of the energy transition, with the proportion of clean energy likely to be less than 20% in 2050. These findings highlight the uneven distribution of energy transition progress across different zones, and suggest urgent interventions are needed, particularly in provinces with high space heating demands, to meet the air quality and climate change goals within the government's announced timeframe.

In 2015, the Beijing-Tianjin-Hebei area, a region with some of the worst air pollution in the world, implemented a large-scale *Clean Heating Policy* to promote rural household energy transition. Figure 2.6 compares the share of clean energy in the rural household sector between the predicted transition, from the ARIMA results, and observed values in 2018 to illustrate the potential effects of the heating energy intervention on the energy transition in C-N. The observed clean energy share in Beijing, Tianjin, and Hebei (shown as red triangles) was about 40%, 40%, and 27% higher than the predicted values, respectively. In contrast, the observed values in the other three provinces in C-N (Shanxi, Henan, and Shandong) without large-scale interventions were similar to the predicted values. These results indicate that the heating intervention may have a significant impact on promoting clean energy in the Beijing-Tianjin-Hebei area. Overall, these findings suggest that large-scale interventions, such as the *Clean Heating Policy*, may be necessary to accelerate the energy transition in highly polluted regions.

From a timeline perspective, the *Clean Heating Policy* has advanced the energy transition by at least 10 years for Beijing, Tianjin, and Hebei compared to the high end of the 95% confidence interval. Even though there are many debates about the program like increased financial burden to households from increased electricity expenditures and energy supply shortages from increased demand on the grid, the *Clean Heating Policy* has shown great effectiveness in driving an energy transition in the rural household sector (Hu, 2021). These results suggest the great potential for interventions to replace the burning of solid fuels for heating through clean energy in driving the rural household energy transition in EC and C provinces.

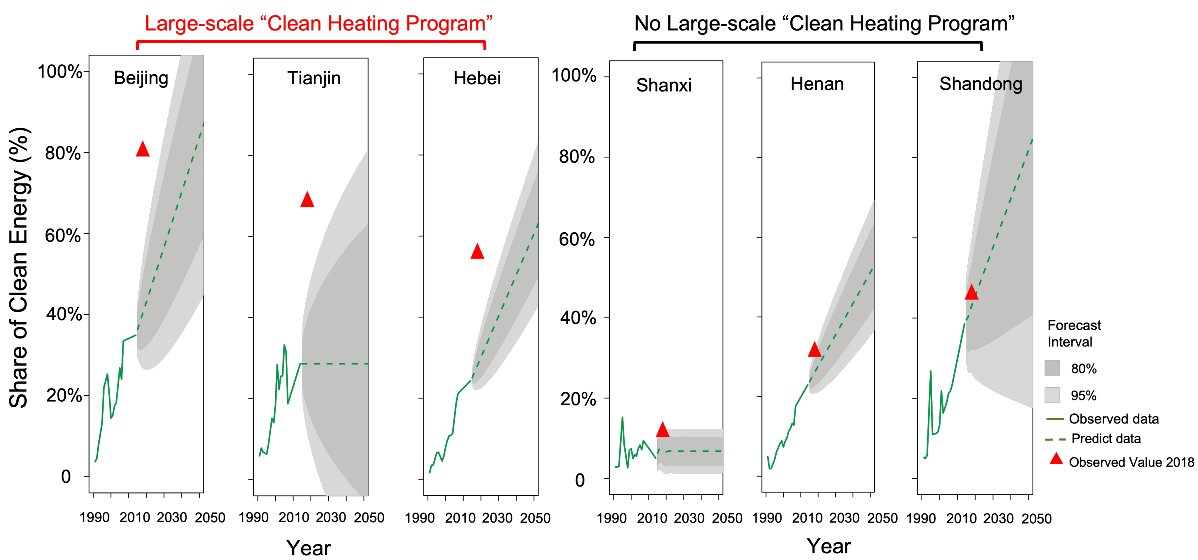


Figure 2.6: Predicted timeline of BAU rural energy transition for C-N provinces. The ARIMA(p, d, q) model predicts rural household energy transitions separately for different provinces, using different parameters. The flat dotted lines of Tianjin and Shanxi provinces indicate no significant temporal patterns, mainly due to the great fluctuation identified in these provinces.

2.3.5 Discussion

The household energy transition is crucial for sustainable development in the developing world. However, the scarcity of high-quality statistical data on rural household energy use, particularly in China, has severely impeded research in this area (Niu et al., 2019). Several issues plague China's statistical data on rural household energy use. Firstly, non-commercial energy sources are omitted. The two primary data sources, the China Energy Statistical Yearbook and the China Rural Statistics Report, ceased publishing biomass fuel consumption quantities after 2008. Furthermore, energy sources like yak dung and solar energy, prevalent in northwestern provinces such as Tibet, Xinjiang, and Qinghai, have never been included in these datasets (Fang & Wei, 2013; Rhode et al., 2007). Consequently, there is limited understanding of these non-commercial energy sources and their roles in energy transition within these provinces. Secondly, there is no distinction between energy activities. Previous studies have highlighted significant disparities in energy use and transition patterns for cooking and space heating (Shen et al., 2022; Tao et al., 2018). However, existing administrative statistics fail to differentiate energy consumption quantities between these activities. To address this issue, we conducted our analysis within the context of the China Rural Domestic Energy Use Zone, aiming to provide indirect insights into the energy transition of different activities. Although datasets such as the WHO's Household Energy Dataset cover relatively long-time scales and differentiate between cooking and heating energy consumption, their sample representativeness could be improved. Thirdly, there is inconsistency in energy indicators. Across the three rounds of the Chinese rural censuses, indicators of domestic energy use varied. The first round excluded electricity as an option, the second round reported primary and secondary cooking, as well as space heating and cooling energy separately, while the third round returned to the primary domestic energy source but also allowed households to select up to two energy sources, including electricity. Such inconsistency severely impedes temporal analysis using census data. Given these challenges with administrative statistics, which are difficult to resolve in the short term, long-term scales based on representative extensive sample survey data will continue to play an essential role in this field.

To address the challenge of data scarcity, we integrated all publicly available administrative statistics along with data from research reports. Despite employing flexible data strategies in various analyses to improve data comparability, the complexity of data sources inevitably introduced uncertainty into our results. However, reassuringly, our diverse data sources exhibited no significant discrepancies in magnitude, with observed past trends aligning with existing studies (Han et al., 2018; Niu et al., 2019; L. Zhang et al., 2009). Nevertheless, this uncertainty regarding historical trends inherently influences our future predictions. Therefore, alongside point estimates, we provide 80% and a more conservative 95% confidence interval. However, it is important to acknowledge that the simple time-series method used for future predictions based on past data also carries its uncertainties, particularly when dealing with limited data, as seen in our C-N six-province forecasts. The imperfect differences in data from different sources result in notably wide confidence intervals; therefore, caution must be exercised in interpreting the results of future predictions.

2.4 Conclusion

China's rural household sector has made significant progress toward clean energy over the past three decades, particularly in the last decade. However, the transition has been uneven across regions, with the Extreme Cold (EC) and Cold (C) zone provinces lagging behind the southern provinces. This disparity underscores the challenge of transitioning energy use for space heating purposes. Our regression analysis suggests that achieving a complete transition in the short term based solely on general economic development may be unrealistic for EC provinces. This means that without outside investment and policy intervention, the environmental, health, climate, and development issues caused by solid fuel combustion will continue to persist in these provinces. The *Clean Heating Policy* in Beijing, Tianjin, and Hebei has demonstrated significant potential to drive the energy transition in EC and C provinces. These interventions highlight the importance of investing in clean energy infrastructure and implementing large-scale policies to accelerate the transition in heavily polluted regions. In conclusion, the uneven transition across regions highlights the urgent need for continued efforts in implementing effective policy interventions for space heating. For China to meet its promised timeline and ambitious air quality and climate mitigation goals, it is crucial to accelerate the transition to clean energy in heavily polluted regions.

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Bridging text

Through a series of quantitative analyses of administrative statistics on rural household energy consumption in China, **Chapter 2** highlights the significant challenges associated with the "business as usual" approach to the energy transition of household space heating in rural northern China. A natural transition would result in the share of clean energy for most provinces in northern China, which have intensive winter space heating needs, remaining below 50% in 2050. Therefore, this underscores the necessity and effectiveness of large-scale incentives, such as the *Clean Heating Policy*, in promoting the rural heating energy transition.

Not only in China, but also in many developing countries, interventions are being implemented to promote the transformation of household energy, focusing on clean cooking energy and access to electricity. Examples include the "Pradhan Mantri Ujjwala Yojana Program" in India and the "Solar Home System Program" in Bangladesh. An evaluation of the impacts of the interventions will provide valuable lessons for further promoting sustainable development in the global household energy transition.

Given that modern energy sources are more expensive than solid fuels and considering the low income levels of rural households who bear the transition costs, the following chapter examines how the *Clean Heating Policy* impacts their energy expenditures and space heating, and whether it has led to energy poverty. In **Chapter 3**, we employ the difference-in-differences method to provide empirical evidence on the impact of the *Clean Heating Policy* on energy poverty based on the field survey data collected from over 1,000 households in Beijing between 2018 and 2022.

Chapter 3

Expenditure versus comfort: distributional impacts on household space heating energy transition program in rural China

This chapter is being prepared for submission to a journal as: Xiang Zhang, Christopher P. Barrington-Leigh, Brian E. Robinson et al., "Expenditure versus comfort: distributional impacts on household space heating energy transition program in rural China."

Abstract

The unaffordability of essential energy services, often termed "energy poverty," poses a significant challenge during the transition from solid fuels to more expensive modern energy sources. We present quasi-experimental evidence of the impacts of household energy transition on energy poverty by leveraging a natural experiment: the staggered implementation of the *Clean Heating Policy* in rural northern China. Between 2017 and 2021, over 36.3 million rural households were prohibited from using coal and were offered subsidies to offset the costs associated with adopting modern energy sources, such as electricity or natural gas, and acquiring necessary heating equipment. Our analysis utilizes field survey data on economic and physical measures of energy poverty from over 1,000 rural households, collected around the years of the *Clean Heating Policy* implementation in Beijing. We employed a difference-in-differences identification strategy to assess the program's effects. Our findings indicate that, under the government's generous subsidy scheme, despite a 14% average increase in winter energy expenditure, there was a notable improvement in space heating quality, as evidenced by indoor temperature, the proportion of the house heated, and heating duration. However, the financial burden was more pronounced for households in high-altitude villages, those with poorer prior heating infrastructure, and those with lower wealth. A straightforward calculation suggests that the majority response of "paying slightly more for significantly improved heating comfort" would have been radically different with lower government subsidies.

3.1 Introduction

Approximately 3 billion people, predominantly among the world's poorest, continue to rely on burning solid fuels such as wood, animal dung, and coal in inefficient and polluting stoves for cooking and space heating (WHO, 2014). Household air pollution from these fuels represents a major environmental health risk, contributing to approximately 2.3 million deaths worldwide in 2019 (95% Confidence Interval (CI): 1.6–3.1 million) and ranking as a top contributor to disability-adjusted life-years (DALYs) in low- and middle-income countries (Global Burden of Disease Collaborative Network, 2020; Lee et al., 2020). Beyond the health impacts, reliance on solid fuels hinders development by reducing labor participation among women and limiting educational opportunities for children (Biswas & Das, 2022; M. Li & Zhou, 2023). Transitioning to modern energy sources, such as electricity and gas fuels, is essential to mitigate these adverse effects and promote sustainable development. This transition is a key aspect of Sustainable Development Goal 7, which aims to ensure access to affordable, reliable, sustainable, and modern energy for all by 2030 (Salvia & Brandli, 2020).

Households' decision to transition to modern energy sources is influenced by a complex mix of a complex mix of exogenous (external conditions) and endogenous (household characteristics) factors (Kowsari & Zerriffi, 2011). Exogenous factors, such as the physical environment, energy supply conditions, policies, and available technologies, significantly affect the accessibility and affordability of modern energy options. For example, urban households and those in milder climates often transition to modern energy more easily, whereas rural households and those in colder regions with higher heating needs face more substantial barriers (Das et al., 2014; Pachauri & Jiang, 2008; Shen et al., 2022). Challenges such as unreliable energy supplies and inadequate infrastructure further complicate the transition, perpetuating dependence on traditional fuels (Masera et al., 2000; Mensah & Adu, 2015; Van der Kroon et al., 2013). On the other hand, endogenous factors mostly influence energy choices through household capabilities and preferences. A substantial body of literature has discussed how financial status (e.g., income), education level, family size, age, gender structure, and lifestyle habits relate to household energy transition (Guta et al., 2022; Han et al., 2018; Lewis & Pattanayak, 2012; Liao et al., 2021).

Despite gradual progress in household energy transitions across developing countries, driven by enhanced energy access and economic growth, the pace of change remains too slow to achieve climate and sustainable development goals (IEA et al., 2023; X. Zhang et al., 2024). In response, many developing nations have launched large-scale household energy intervention projects (IEA et al., 2021; Quinn et al., 2018). Noteworthy initiatives include India's "Pradhan Mantri Ujjwala Yojana Program," which provided 80 million free liquefied petroleum gas (LPG) connections to promote clean cooking (Ranjan & Singh, 2020), and Ecuador's "Program for Energy Efficient Cooking," offering consumer credit for induction stove purchases and free electricity to over 670,000 households (Gould et al., 2018; Shankar et al., 2020). However, programs specifically targeting clean heating remain limited (World Health Organization, 2021). A significant exception is China's *Clean Heating Policy* (农村冬季清洁取暖), launched in 2013, which has become the world's largest effort to curtail coal use for household heating (X. Zhang et al., 2019). From 2017 to 2021, the policy extended to over 36.3 million rural households in northern China, with further expansion planned to reach an additional 21 million households by 2025 (Dispersed Coal Management Research Group, 2023). This government-led initiative employs a comprehensive strategy, including banning coal supplies to rural areas and subsidizing both clean heating equipment and energy costs. The transition primarily involves moving from coal-based to electric heating with air-source heat pumps (*Coal to Electricity* (煤改电)), with a smaller segment adopting natural gas heating systems (*Coal to Natural Gas* (煤改气)).

While these interventions are intended to speed up household energy transitions and address environmental concerns, they also present challenges concerning safety, affordability, and equitable access (Carley & Konisky, 2020; Feenstra & Clancy, 2020; Hu, 2021; C. Liu & Wei, 2021; Wu et al., 2017). Modern energy sources, though cleaner, are generally more expensive than traditional solid fuels, potentially making them unaffordable for low-income households and exacerbating energy poverty (R. Ma et al., 2022; Nguyen et al., 2019). Energy poverty is defined as the inability to afford adequate space heating and other essential energy services due to high costs (Healy & Clinch, 2004; Howden-Chapman et al., 2012).

The concept of energy poverty is often used interchangeably with fuel poverty in the literature to describe concerns related to the deprivation of household energy consumption. However, some studies distinguish between the two concepts based on their context of application (developing vs. developed countries), recognition, driving forces, and expression (Bouzarovski & Petrova, 2015). As K. Li et al. (2014) points out, some cold regions, such as rural northern China, India, and Nepal, experience both energy poverty and fuel poverty due to limited access to energy or advanced cooking and heating technologies, as well as households there struggle to achieve adequate home heating at an affordable cost. Considering this reality, we adopt the more widely accepted term "energy poverty" in this paper to represent the challenges that the *Clean Heating Policy* pose to rural households.

The measurement of energy poverty requires a multi-dimensional approach that considers economic factors, the adequacy of heating, and the specific needs of vulnerable groups (Boardman, 2013, p. 23).

The economic measurement of energy poverty is commonly indicated by the proportion of household income spent on energy (Aristondo & Onaindia, 2018; Hills, 2012; Moore, 2012; Nussbaumer et al., 2012; Okushima, 2017; Riva et al., 2024; Q. Wang et al., 2021). Historically, the definition proposed by Boardman (1991), suggesting that households experiencing energy poverty spend more than 10% of their income on energy, has been widely accepted. This benchmark was derived from patterns observed among the lowest-income 30% of households in a 1988 UK survey (Liddell et al., 2012). Another commonly used method for determining the energy poverty threshold is the "twice-median measure (2M)," which defines households as experiencing energy poverty if their energy expenditure as a share of income exceeds twice the median level within the population (Charlier & Legendre, 2021; Debanné et al., 2025; Isherwood & Hancock, 1979). Following the "2M" method, Xie et al. (2022) rural households in Beijing and Hebei were considered to be in energy poverty if their heating expenditure to income ratios exceeded 7.3% and 8.0%, respectively.

Given the limitations of model simulations, which often simplify household energy consumption and neglect the real-world financial constraints impacting fuel use behaviors, field surveys are crucial for a thorough understanding of the economic effects of energy interventions on energy poverty (Hutton et al., 2007; Jeuland et al., 2015; H. Liu & Mauzerall, 2020; T. Ma et al., 2023; Pillarisetti et al., 2017; Zhao et al., 2021). For instance, M. Li et al. (2021) employ a generalized Roy model to analyze data from 88 villages across 11 provinces in China, spanning the years 2005 to 2008. They find that transitioning to LPG increased household energy expenditures by 65–80%. Additionally, Xie et al. (2022) conducted a survey of approximately 4,500 rural households in Beijing and Hebei provinces. They estimated that by the end of 2017, the implementation of the *Coal to Electricity* and *Coal to Natural Gas* policies resulted in an increase of 46,300 and 353,300 households, respectively, falling into energy poverty, as their heating expenditure-to-income ratios exceeded the established energy poverty lines.

Defining energy poverty solely by the proportion of income spent on energy, has a significant limitation: it overlooks the intricate balance between energy costs and the actual fulfillment of energy needs. Vulnerable groups such as rural residents, low-income households, and the elderly face tough decisions amid rising fuel costs. Common coping strategies include limiting heating to certain rooms or times, wearing extra clothing, or resorting to less efficient and potentially harmful practices like burning biomass (Anderson et al., 2012; Chard & Walker, 2016; Charlier & Legendre, 2019; Harrington et al., 2005; Mottaleb, 2021; Wright, 2004). To capture a more comprehensive picture of energy poverty, it is essential to incorporate indicators that measure space heating alongside economic measures (Moore, 2012).

Indoor temperature, for example, is a direct indicator of space heating adequacy and is critical for physical and mental well-being, especially during winter (Al horr et al., 2016; Janssen et al., 2023). The World Health Organization (WHO) recommends maintaining a minimum indoor temperature of 18°C for general populations during the cold seasons (World Health Organization, 2018). However, a survey in rural Chinese households showed that 40%

of respondents felt cold or extremely cold during the day and 60% at night, indicating indoor temperatures well below 15°C (Shan et al., 2015). Additional metrics like heating duration and the proportion of homes with heating provide deeper insights into the complexities of energy poverty (Boardman, 2013; Simcock & Walker, 2015). Our pilot study involved 302 rural households across three districts in Beijing and sought to explore the effects of the *Coal to Electricity* policy. By comparing cross-sectional data from households that received the intervention to those that did not, Barrington-Leigh et al. (2019) find that households that made the switch experienced improved heating outcomes, such as higher indoor temperatures and longer heating durations. This occurred even though these households faced higher energy expenditures during the heating season.

This paper provides empirical evidence on the impact of household energy transition on energy poverty by addressing the following research questions. First, from both economic and physical measurement perspectives, does the *Clean Heating Policy*, on average, alleviate or exacerbate household energy poverty? Second, beyond these average impacts, how do the effects persist over time? The impact of energy intervention programs on households often varies considerably depending on socioeconomic factors and housing characteristics (Andadari et al., 2014; Giuliano et al., 2020). Considering different household characteristics and distributional effects, how does the impact of the *Clean Heating Policy* on energy poverty vary across different household subgroups? To reduce the financial burden on households, the government provides substantial subsidies on energy prices. If government subsidies were to decrease in the future, how might this affect policy impacts?

We find that the *Clean Heating Policy* has a significant positive impact on rural households' space heating in terms of indoor temperature, the number of rooms heated regularly, and the average duration of heating, alongside a slight increase in winter expenditure. After the implementation of the *Clean Heating Policy*, per capita winter energy expenditure increased by approximately 180 RMB. The economic impacts are more pronounced for rural households living in high-altitude villages; per capita winter energy expenditure increased by approximately 208 RMB for every 100-meter increase in village altitude. The widespread adoption and expansion of the radiator system have significantly contributed to these improvements in space heating. Moreover, despite facing greater financial challenges, even less wealthy households experienced enhanced thermal comfort following the implementation of the *Clean Heating Policy*.

The remainder of the paper is organized as follows. In Section 3.2, we describe the data regarding the study design, sampling strategy, and collection. Section 3.3 lays out the identification strategy. Section 3.4 presents the baseline results, heterogeneity analysis and robustness checks. Section 3.5 discusses potential impacts under different policy scenarios. Finally, Section 3.6 concludes.

3.2 Data

In this section, we detail the study design, sampling strategy, and data collection methods used to gather first-hand household survey data for our empirical analysis.

3.2.1 Background and study design

Our field research was conducted in Beijing, historically one of the world's most air-polluted regions and the initial site for the *Clean Heating Policy* (X. Zhang et al., 2019; Y.-L. Zhang & Cao, 2015). In early 2013, during the heating season, Beijing faced a severe haze crisis, with hourly $PM_{2.5}$ levels sometimes exceeding 1,000 $\mu g/m^3$ — over 40 times the WHO recommended limit (Q. Zhang et al., 2019). This critical situation led to the implementation of the *2013–2017 Clean Air Action Plan* (北京市 2013–2017 年清洁空气行动计划) in September 2013, which enforced rigorous pollution control measures across various sectors. A key element of this legislation was the *Clean Heating Policy*, aimed specifically at the rural residential sector (H. Zhang et al., 2016).

Beijing's heating season, lasting from November 15th to March 15th, experiences temperatures that can plummet to around -15°C, necessitating significant heating efforts. In rural areas, decentralized heating methods are prevalent, including the use of coal stoves with water radiator system, wood-burning kangs (brick beds heated by internal hot smoke), and traditional coal stoves (Building Energy Research Centre at Tsinghua University, 2012; X. Li et al., 2022; Zheng & Bu, 2018; Zhuang et al., 2009). According to official statistics from 2012, before the *Clean Heating Policy* was initiated, approximately 2.86 million rural residents consumed 2.1 million tonnes of coal in Beijing. However, these figures may underestimate the actual consumption due to the Yearbook's top-down approach to compiling energy balance statistics (Cheng et al., 2017). Empirical studies have estimated that emissions from rural household space heating contribute to 70% of $PM_{2.5}$ and 60% of SO_2 emissions during the winter (Cai et al., 2018).

Launched in 2013, the rural *Clean Heating Policy* in Beijing initially targeted suburban areas, designating 160 villages as pilot sites for the transition from coal to electricity. By 2018, the policy had significantly expanded to include 2,963 villages in the plains, with 80% of these villages switching to electricity and 20% to natural gas (Xinhua Net, 2019). That same year, the policy also began pilot initiatives in mountainous villages (Xinhua Net, 2018). A decade after its inception, by 2023, the *Clean Heating Policy* has achieved remarkable coverage, reaching over 90% of villages and 95% of rural households in Beijing (China Energy News, 2023).

In mountainous regions, where extending natural gas pipelines is challenging, *Coal to Electricity* has become the predominant technological solution for most households (The People's Governemnt of Beijing Municipality, 2018). In Beijing's *Coal to Electricity* policy, households received subsidies for new heating equipment based on their heated area (200 RMB/m^2) up to 24,000 RMB.[1] Additionally, they benefit from a discounted winter electricity tariff of 0.1 RMB/kWh, significantly lower than the regular price of 0.48 RMB/kWh, for up to 10,000 kWh used between November 15th and March 15th (H. Liu & Mauzerall, 2020). However, the policy encounters unique challenges in mountainous areas due to the colder temperatures and significant daily temperature fluctuations, which increase heating demands

[1] Based on the March 2024 exchange rate, 1 RMB $\approx$ 0.14 US dollars.

and reduce the efficiency of air-source heat pumps (Xu et al., 2019). These conditions may exacerbate energy poverty among households.

In addition to altitude, the existing housing conditions within a village significantly influence the government's decision to include it in the *Clean Heating Policy*. The quality of housing, particularly insulation, directly impacts household energy expenditures and the effectiveness of the heating program (Besagni & Borgarello, 2018; Riva et al., 2021; Salari & Javid, 2017). To be eligible, houses must have undergone insulation renovations, and the village must not be slated for demolition or major renovations within the next five years according to regional plans. Before making final decisions, village committees assess households' willingness to participate in the policy and communicate this information to higher levels of government for consideration. Thus, the affordability of the policy for households could indirectly influence the government's decision-making process.

For villages not yet included in the *Clean Heating Policy*, the *Reduce and Substitute Coal Program* (北京农村地区村庄 "减煤换煤") provided comprehensive coverage by 2017. This initiative mandated the end of low-quality bulk coal burning and promoted the use of high-quality coal briquettes provided by the government. As a result, for households incorporated into the *Clean Heating Policy* after 2017, their counterfactual heating scenario involved using briquettes supplied through the *Reduce and Substitute Coal Program*. The acquisition process for these briquettes entails village committees collecting household orders in the autumn and forwarding them to higher government authorities. The briquettes are then purchased at a uniform price within the county and distributed to households before the heating season starts. In contrast to the relatively low-quality bulk coal, priced at about 800 RMB per tonne, the market price for these high-quality coal briquettes is around 1,300 RMB per tonne. To ease the financial burden on households, municipal subsidies of 200 RMB per tonne, and district and county subsidies ranging from 200 to 500 RMB per tonne, are provided (Beijing Daily, 2015).

Our field study occurred through three survey rounds spanning four years. The baseline survey was conducted between December 2018 and March 2019, preceding the implementation of the *Clean Heating Policy* across all sample villages. The first follow-up survey took place one year later, between November 2019 and January 2020. Due to the COVID-19 pandemic, the second follow-up survey was delayed until November 2021 to January 2022. This longitudinal data collection approach provides an opportunity to understand the causal impact of the policy on the sampled villages based on quasi-experimental methods.

3.2.2 Sampling

Our study was conducted across four peri-urban districts of Beijing — Fangshan, Huairou, Mentougou, and Miyun — known for a high prevalence of rural households using solid fuels such as briquettes and firewood for heating. We selected 50 villages to represent a diverse range of socioeconomic and geographic condition that had not yet entered the *Clean Heating Policy* at the time of our baseline survey. Figure 3.1 shows the locations and the timing of treatment for these sample villages. Initially, none of the villages were part of the *Clean Heating Policy*. By the time of our first follow-up survey, 10 villages had been incorporated into the policy. Over the next two years, leading up to the second follow-up survey, an additional 10 villages joined the policy — seven in 2020 and three in 2021. Thus, by the end of our study period, 20 out of the 50 villages were participating in the policy.

In each village, we utilized a semi-random selection process to identify approximately 20 households for inclusion in the study. This method was necessary due to lower occupancy rates during the winter, which made a fully random selection impractical. To ensure data collection from occupied households, we collaborated with village leaders who provided insights into which households were present at the time of our visits. Then, among the households that were at home on the day of our visit, we randomly selected 20 households in each village. The study commenced with a baseline survey involving 977 households. Anticipating potential sample attrition due to absenteeism, refusals, or mortality among respondents, we strategically incorporated new households in each subsequent survey round. As a result, the first and second follow-up surveys included 1,055 and 1,012 households, respectively. A total of 733 households consistently participated across all three survey rounds. Figure B.1 in Appendix B.1 provides a detailed breakdown of revisited and newly added households.

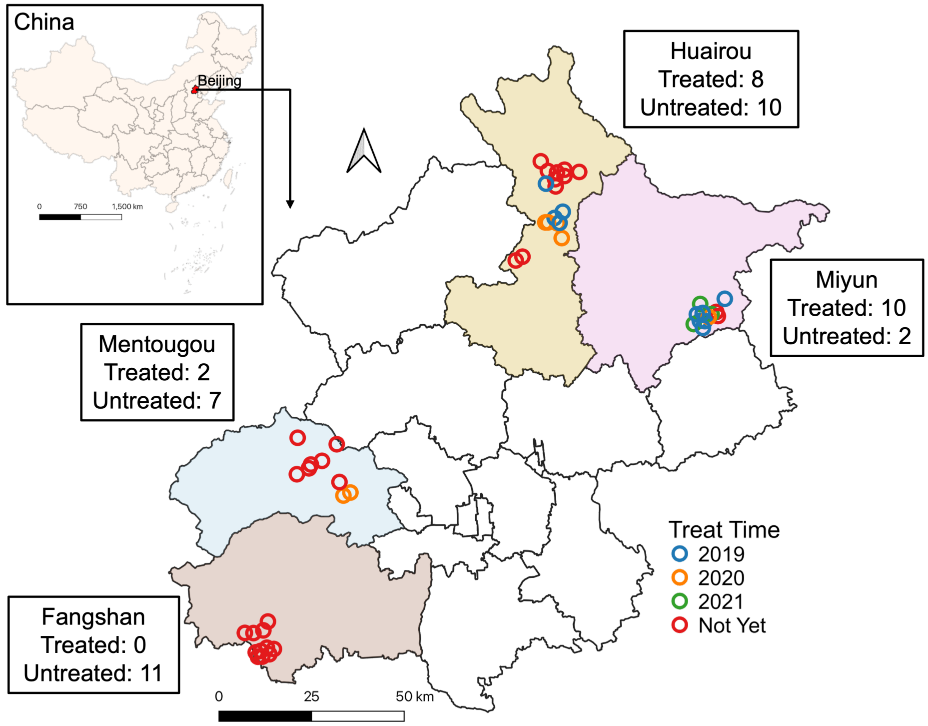


Figure 3.1: Sampling strategy and treatment status of sample villages.

3.2.3 Data collection

All surveys were conducted on tablet computers running Surveybe and ODK software. Leveraging an interdisciplinary collaboration, we conducted a sequence of surveys aimed at constructing a comprehensive panel dataset encompassing variables pertinent to fuel consumption, space heating, subjective well-being, health, and air quality. In this section, we provide a succinct overview of the principal variables examined in this study.

We gathered data on a range of sociodemographic characteristics for each household. This included details on household composition such as family size, age, and gender of members; demographics including education level, marital status, employment, and occupation; economic factors like income and assets; and consumption patterns, which covered expenditures on items like meat and communication services.

To assess winter fuel consumption, our survey posed detailed questions about the types of fuels used during the heating season, their specific applications (e.g., for cooking, space heating, or water heating), the quantities consumed, and their market prices.[2] Given the difficulties households face in accessing accurate electricity usage data and the complexity of the tariff system — particularly with subsidies under the *Clean Heating Policy* — we asked respondents to estimate their total electricity expenditure for the winter heating season.

Through a series of questions, we systematically gathered data on household space heating through various measurements. First, we deployed temperature sensors in the room where people spent the most time each day in winter for a subset of sample households. These sensors continuously recorded indoor temperatures at regular intervals (every 125 minutes) throughout the entire heating season, as detailed in our prior research (see Sternbach et al. (2022) for further information). Additionally, to provide a comprehensive overview of household space heating practices, we documented the duration of heating, occupancy patterns, and all heating methods employed, along with the corresponding durations, for each room.

Alongside household data, we assembled village-level information. Treatment status was gathered through interviews with village leaders. Altitude data for each village was derived from Google Earth, utilizing GPS coordinates of village committee locations recorded during fieldwork. Distances from sampled villages to central Beijing were calculated as linear distances using Baidu Maps. Socioeconomic data at the village level, including number of households, population, and per capita income, were sourced from the 2016 statistical yearbook of the four study districts. This socioeconomic data offers a snapshot of village characteristics in 2015, prior to the *Clean Heating Policy* implementation in mountainous areas.

[2]This analysis focuses solely on market prices. The time households spend gathering biomass fuels like firewood and straw is not included in the price calculations.

3.3 Identification strategy

To assess the impacts of the *Clean Heating Policy* on energy poverty, we utilize the difference-in-differences (DiD) method, a well-established approach for policy evaluation. This method relies on the crucial "parallel trends" assumption, which posits that the treatment and control groups would have experienced similar changes in their outcomes over time in the absence of treatment. Consequently, by comparing the before-and-after differences in the control group, we can estimate the counterfactual outcome for the treatment group. Our analysis focuses on the relative changes in energy expenditure and space heating indicators, comparing households that participated in the policy to those that did not, across the pre-treatment and post-treatment periods.

3.3.1 Two-way fixed effects DiD estimator

Our DiD estimation departs from the conventional two-group, two-period design, leveraging data collected over multiple years and incorporating varying treatment timings. This staggered implementation of the policy offers the potential for richer insights into its effects on energy poverty. Specifically, we employ the following two-way fixed effects (TWFE) regression model:

$$Y_{it} = \beta \times \mathrm{Treat}_{it} + X_{it} \times \gamma + \mu_i + \lambda_t + \epsilon_{it} \tag{3.1}$$

where the outcome of interest, denoted Y_{it}, is either the winter energy expenditure or space heating indicators (i.e., indoor temperature, number of rooms with daily heating, and average duration of room heating) of household i in year t. The variable Treat_{it} is the treatment status for household i in year t. Specifically, $\mathrm{Treat}_{it} = 1$ if the household i is involved in the *Clean Heating Policy* in year t, $\mathrm{Treat}_{it} = 0$ if the household i does not get the treatment.[3] This equation also includes controls of confounders, X_{it}, that may affect both treatment status and, as outcomes, energy expenditure and space heating. X_{it} includes the building

[3]Since we are dealing with a staggered treatment setting, as shown in Equation 3.1, we use the dummy variable $\mathrm{Treat_{it}}$ to represent the actual treatment status, where $\mathrm{Treat_{it}} = 1$ corresponds to $\mathrm{Treat_i} \times \mathrm{Post_t} = 1$ in the traditional DiD definition.

age and house area, which capture the common housing renovations in rural Beijing in recent years. Building age serves as a useful indicator of both the likely insulation quality of a house and potential plans for its future renovation or demolition. The house area determines the type and power of heating equipment that households can obtain within the scope of government subsidies. Household fixed effects μ_i control for all time-invariant factors that differ across households, year fixed effects λ_t control for any unobserved patterns of that affect all households simultaneously. ϵ_{it} is the error term.

The coefficient of interest in Equation 3.1 is β, which represents the estimated impact of the *Clean Heating Policy* on either economic or space heating outcomes. A positive coefficient indicates that the policy increases household energy expenditure (or improves space heating), while a negative coefficient indicates that the policy reduces expenditure (or space heating). We use the TWFE estimator to estimate the baseline treatment effects.

Besides the average treatment effects, we go beyond the baseline regression and estimate a dynamic version of the TWFE model as shown in Equation 3.2. This event study helps us to understand what the temporal trends are in the impacts of *Clean Heating Policy* as a function of the year of participation.

$$Y_{it} = \sum_{j=1}^{3} \theta_{-j} \times \text{Treat}_{it} + \sum_{k=0}^{2} \beta_k \times \text{Treat}_{it} + X_{it} \times \gamma + \mu_i + \lambda_t + \epsilon_{it} \tag{3.2}$$

The coefficients θ_{-j} measure the difference in the change of outcomes ($j = 1$ is dropped to avoid perfect collinearity) between the treatment and control groups before the *Clean Heating Policy*. Estimating pre-event trends can provide insight into the parallel trend assumption. β_k are coefficients that measure the persistence of impacts on outcomes years after households participate in the *Clean Heating Policy*.

In order to address the distributional impacts, we estimate the heterogeneous treatment effects of the *Clean Heating Policy* on subgroups of households by considering a modified version of Equation 3.1, as depicted in Equation 3.3:

$$Y_{it} = \beta \times \text{Treat}_{it} + \zeta \times \text{Treat}_{it} \times C_i + X_{it} \times \gamma + \mu_i + \lambda_t + \epsilon_{it} \tag{3.3}$$

where C_i represents the specific dimension of village or household heterogeneity we aim to examine. The coefficient ζ captures the differences in treatment effects between the various categories of this moderator variable. We explore various factors that contribute to the heterogeneous treatment effects, including village altitude, baseline household heating infrastructure, and baseline household wealth status. We do not include the C_i in the regression since these village or household time-invariant "moderators" will be absorbed by the household fixed effect term μ_i.

3.3.2 Staggered DiD and heterogeneity-Robust DiD estimators

While the TWFE estimator has been commonly used to estimate average treatment effects in DiD models, recent theoretical research has revealed potential biases when dealing with staggered treatment implementations, as is the case with the *Clean Heating Policy* in our study (illustrated in Figure 3.2). These biases primarily arise from heterogeneous treatment effects, where the impact of the policy may vary across time and/or between the treated units that receive the treatment at different times (De Chaisemartin & d'Haultfoeuille, 2022; Goodman-Bacon, 2021). The TWFE estimator is equivalent to the variance-weighted average of all 2×2 TWFE estimators (e.g., four 2×2 TWFE estimators in three groups of early treat, late treat, and never treat: early treat vs. never treat, late treat vs. never treat, early treat vs. late treat before treatment, and late treat vs. early treat after treatment). Among these comparisons, the "late treated vs. early treated after treatment" is potentially problematic because it involves using the early treated units as the control. The later-treated group must adjust for the outcome changes of the early treated units, which already incorporate the treatment effects, potentially biasing the results (Baker et al., 2022). Consequently, to obtain unbiased estimates using TWFE, additional assumptions regarding the temporal homogeneity of treatment effects are required in addition to the parallel trend assumption (De Chaisemartin & d'Haultfoeuille, 2022). However, the assumption of a constant intervention effect over time is often unrealistic.

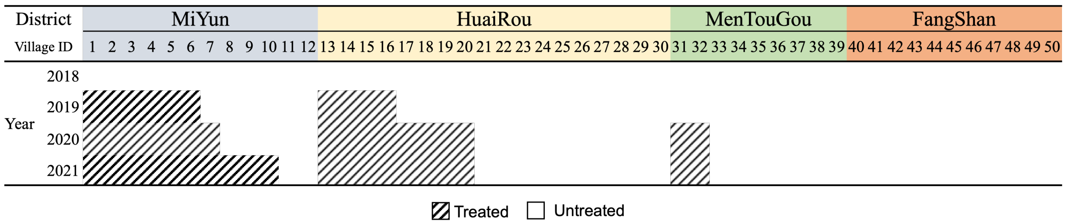


Figure 3.2: Treatment timing of the *Clean Heating Policy* in sample villages.

To mitigate potential bias of the traditional TWFE estimator, several new heterogeneity-robust DiD estimators have been proposed. By adopting various strategies to account for variations in treatment effects and eliminating the problematic 2×2 DiD comparisons between later treated and early treated units, these robust estimators provide consistent estimates even in the presence of heterogeneous treatment effects across time and/or treated units (Wing et al., 2024). To address concerns regarding our baseline TWFE estimation, we replicated our event study results using robust estimators introduced in recent studies (Borusyak et al., 2021; Callaway & Sant'Anna, 2021; De Chaisemartin & d'Haultfoeuille, 2024; Gardner, 2022; Sun & Abraham, 2021; Wooldridge, 2021). A comparison of TWFE and other new heterogeneity-robust DiD estimators for the average treatment effects on all outcomes is provided in Figure B.2 in the appendix.

A priori, one threat to the parallel trend assumption in our study is the unique situation in Fangshan district. Notably, during the second follow-up season, the price of coal briquettes doubled exclusively within the Fangshan district, where no sample village had access to the *Clean Heating Policy* throughout the study period. This price increase was due to Fangshan's distinct subsidy approach under the *Reduce and Substitute Coal Program*. Unlike in the other three districts, where government subsidies offset the market price increases of briquettes, allowing households to pay a consistent price over time, the Fangshan government provided a fixed subsidy amount. As a result, when prices increased in 2021, households in Fangshan had to cover the additional costs themselves. To maintain a reliable counterfactual for the treated households and uphold the parallel trend assumption, we chose to exclude observations from the last season in Fangshan from our analysis. This decision is based on the rationale that energy expenditures in Fangshan last season would not mirror those treated households in other districts without the influence of the *Clean Heating Policy*.

3.4 Results

Our study focuses on evaluating the impacts of the *Clean Heating Policy* on household energy poverty. Specifically, we analyze two crucial categories of energy poverty outcomes. The first category includes economic indicators such as winter energy expenditure and its proportion of household income. The second category encompasses physical measures like indoor temperature, the number of rooms heated daily, and the average duration of room heating.

3.4.1 Descriptive statistics

Table 3.1 presents summary statistics for key variables across three groups: those never exposed to the *Clean Heating Policy*, those in treated villages before policy implementation, and those in treated villages after implementation. Compared to the never-treated group, households in treatment villages spent slightly less on winter energy before the policy, but they did not heat as much of their space, as reflected in lower indoor temperatures, fewer rooms with regular heating, and shorter average heating duration. For households in the treated villages, winter energy expenditures prior to treatment averaged 1,174 RMB per person. Even when considering only the energy expenditure during the heating season, which accounts for 10.8% of family annual income, this figure exceeds the 7.3% threshold of energy poverty proposed by Xie et al. (2022) for rural households in Beijing. After the adoption of clean heating, expenditures increased to 1,587 RMB per capita, marking an approximate 1% rise in the proportion of income dedicated to energy expenses. From these descriptive statistics, the *Clean Heating Policy* appears to have marginally worsened household energy poverty.

The proportion of income spent on winter energy by households in our study (about 11%) exceeds the figures reported in existing research on energy poverty among rural Chinese households (R. Wang & Jiang, 2017). For instance, Wu et al. (2019) found that rural households in provinces with substantial heating needs typically spend about 5% of their income on energy, with this figure rising to over 6% in Beijing. This discrepancy can primarily be attributed to the geographical and socioeconomic characteristics of the sample; most of the villages not yet included in the *Clean Heating Policy* as of 2018, the start of our study, are situated in remote, mountainous areas of Beijing. These areas not only have lower incomes but also higher heating demands, which contribute to the increased proportion of income dedicated to energy expenditure.

Despite allocating a significant portion of their income to winter energy expenses, households experienced inadequate space heating prior to the intervention. We assessed space heating primarily through nighttime indoor temperatures (from 5 pm to 7 am) in January for two main reasons. Firstly, January is typically the coldest month in Beijing, with eight of the past ten years (2013–2022) experiencing their lowest average monthly temperatures during this period. For instance, January 2021 recorded an average temperature of −3.6°C, with the year's lowest temperature, −19.6°C, on January 7th (Beijing Municipal Bureau of Statistics, 2014 – 2023). Secondly, the significant drop in outdoor temperatures after sunset, often by up to 10°C compared to daytime highs, highlights the critical need for effective heating during nighttime. Without the *Clean Heating Policy*, the average indoor temperature in our sampled households was only 13.1°C, substantially below the WHO-recommended minimum of 18°C, clearly illustrating the inadequacy of space heating in many rural households.

Before the implementation of the *Clean Heating Policy*, households in our study typically heated only 4 out of 8 rooms regularly, indicating that less than half of their living space was adequately heated. Furthermore, the average heating duration per room was merely 9 hours, severely limiting comfortable living conditions during the winter months. These space heating indicators, as outlined by Boardman (2013), suggest that our sample households were experiencing energy poverty prior to the intervention. However, following the implementation of the *Clean Heating Policy*, we observed significant enhancements in space heating across all indicators. This marked improvement points to a substantial reduction in energy poverty, significantly enhancing both the adequacy and comfort of heating within these households.

Houses in both the never-treated and treated groups have similar ages, with an average construction year of around 2005. However, the average house size in the treated group is notably larger, measuring approximately 135 m^2, about 15 m^2 more than those in the never-treated group. Geographically, treated villages are located at a slightly lower average altitude of 280 meters and are positioned an average of 7.5 kilometers farther from Beijing's city center than never-treated villages. There are also differences in social characteristics: treated villages tend to have fewer households and a smaller population, yet they exhibit a per capita income in 2015 that was 44% higher than that of never-treated villages. This significant income discrepancy is primarily due to the socioeconomic profile of 11 never-treated villages located within a town on the border of Beijing and Hebei province, in the Fangshan district, where per capita income is notably lower than in the villages sampled in the other three districts.

Table 3.1: Descriptive statistics. Data on village characteristics are obtained from the 2016 statistical yearbook of the selected four districts, providing insights into the characteristics of the year 2015, prior to the implementation of the *Clean Heating Policy*. These "baseline" statistics do not vary over time. A balance test of the key variables between never-treated and treated households before the treatment, conducted using two-sample mean t-tests, is presented in Table B.1.

Variable	Never Treated			Treated					
				Before Treatment			After Treatment		
	Obs	Mean	SD	Obs	Mean	SD	Obs	Mean	SD
Economic Outcomes									
Per Capita Winter Energy Expenditure (Exp: RMB/person)	1512	1340	910	578	1170	764	597	1590	939
Share in Family Income (Share: %)	1512	11.0	11.9	578	10.8	11.7	597	11.9	13.0
Space Heating Outcomes									
Nighttime Indoor Temperature (Temp: °C)	730	14.0	3.72	228	13.1	4.13	284	15.9	3.46
Rooms with Regular Heating (Rooms)	1505	4.48	2.62	577	3.96	2.45	595	5.93	3.12
Average Heating Duration (Duration: hours $\cdot$ day^{-1} $\cdot$ room^{-1})	1505	11.0	5.88	577	9.25	5.71	595	12.6	4.87
Controls									
Building age (years)	1512	16.5	14.9	578	14.6	13.1	597	15.3	12.6
Building area (m^2)	1512	118.8	50.8	578	134.7	53.4	597	141.2	58.4
Selected Village Characteristics[1]									
Altitude (m)	30	292	130	20	282	58.3	/	/	/
Distance to Beijing (km)	30	73.6	18.6	20	81.1	11.4	/	/	/
Number of households	30	375	401	20	232	172	/	/	/
Village Population	30	662	678	20	512	423	/	/	/
Per Capita Income (10^3 RMB/person)	30	12.9	5.22	20	18.6	3.39	/	/	/
Number of Villages		30					20		
Number of Households		695					485		

3.4.2 Main results

Table 3.2 presents the estimates of the treatment effect of the *Clean Heating Policy* on various energy poverty measures across different specifications. We employ TWFE with fixed effects terms of year and policy expansion timing group in column 1, year and village fixed effects in column 2, year and household fixed effects in column 3, and household-level time-varying control variables in column 4. Our baseline estimations are consistency across these specifications, especially when accounting for village/household and year fixed effects. These results align with the treatment effects estimated using heterogeneity-robust DiD estimators, as depicted in Figure B.2 in Appendix B.3.

We first examine the impacts of the *Clean Heating Policy* on household winter energy expenditure. Typically, clean energy sources like electricity and gas are more expensive than solid fuels such as coal and biomass. Therefore, adopting clean energy for heating often translates to increased costs. This rise in energy expenditures can strain household budgets, potentially compromising their ability to afford basic energy needs and allocate resources for other essential goods and services. In this section, we examine the impacts of the *Clean Heating Policy* on household winter energy expenses, as well as the share of these expenses in household income, within the context of the government's "triple subsidies" shown in Figure B.3 in the appendix.

The complete baseline specification, as shown in Panel A column 4, indicates that the *Clean Heating Policy* leads to an average increase in per capita winter energy expenditure of 182 RMB (95% CI: 18.4–345.0 RMB). When compared to households not enrolled in the policy, which spent an average of 1,344 RMB, this represents an approximate 13.5% increase in per capita winter energy expenditure. Furthermore, this escalation in expenditure translates to about a 2% increase (95% CI: −0.2–4.1%) in the share of annual household income dedicated to winter energy, causing households to spend, on average, 12% of their yearly income to cover these costs.

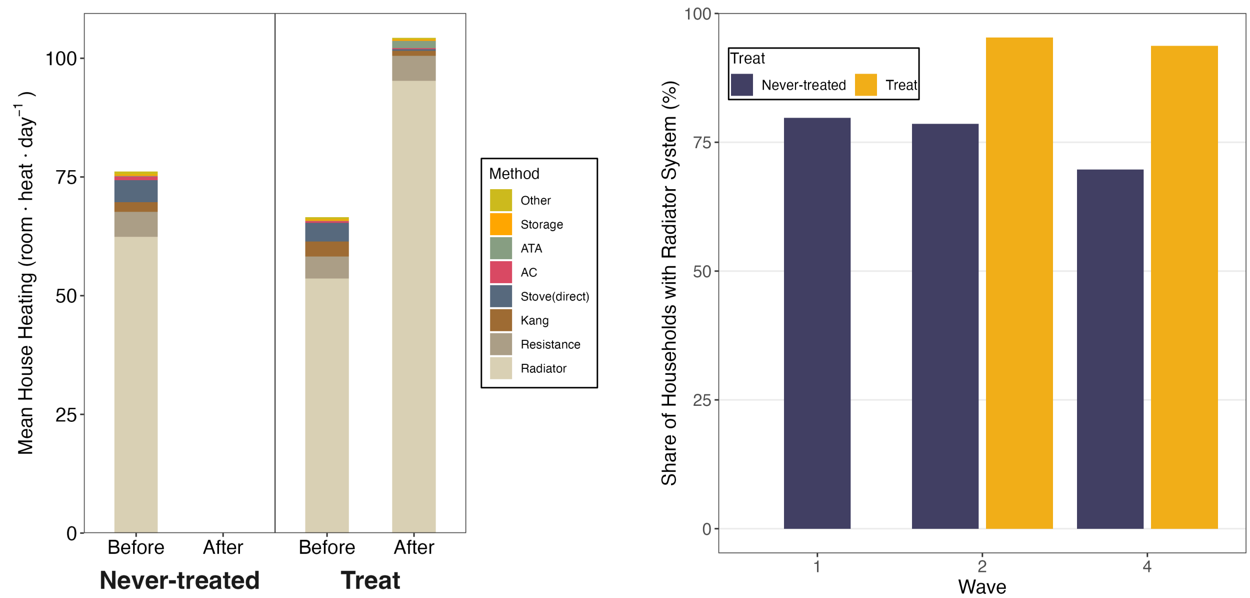
Due to the high heating costs and an unreliable energy supply, particularly for the *Coal to Natural Gas* conversion, there have been repeated controversies each heating season regarding the risk of rural households in North China freezing (Hu, 2021). We explore the average treatment effects of the *Clean Heating Policy* on space heating from various perspectives. Initially, we analyze the nighttime indoor temperature of the room where households spend most of their time during winter. As shown in Panel B column 4 of Table 3.2, the implementation of the *Clean Heating Policy* resulted in an increase in nighttime indoor temperature by 1.8°C (95% CI: 0.9–2.7°C), suggesting that treated households could achieve an average indoor temperature of about 15°C. While this temperature is still below the WHO's recommended thresholds, the substantial impact of indoor temperature on health indicators, including blood pressure and respiratory health, highlights the crucial benefits of this increase for older populations living in cold, rural areas (Saeki et al., 2014; Sternbach et al., 2022).

In addition to the primary living spaces, the heating of other areas within a home is crucial for the various activities conducted during winter. Our evaluation of the *Clean Heating Policy* considered its impact on the number of rooms receiving regular heating and the average duration of heating per room. Prior to the policy, less than 50% of the rooms in a house — typically only 4 — received regular heating. According to Panel B column 4 of Table 3.2, the policy led to a rise in both the number of rooms with regular heating and the duration of room heating. Specifically, there was an increase of 1.4 rooms (95% CI: 1.0–1.7 rooms) having daily heating and an extension of 3.2 hours (95% CI: 2.2–4.2 hours) in the duration of room heating.

Table 3.2: Baseline results. Each column estimates Equation 3.1 with a unique specification. The difference in observations between specifications are due to singleton observations (households appearing in only one survey round), some observations were dropped when including household fixed effects in the analysis. Standard errors in parentheses are clustered at the village level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	TWFE 1	TWFE 2	TWFE 3	TWFE 4
Panel A. Economic Outcomes				
Per capita Winter Energy Expenditure (RMB)				
Treatment	269.29***	207.87***	175.24**	181.71**
	(79.83)	(77.34)	(83.60)	(83.31)
Share of Winter Energy Expenditure in Income (%)				
Treatment	2.52**	1.97*	1.98*	1.99*
	(1.01)	(1.04)	(1.08)	(1.09)
Num.Obs.	2687	2687	2497	2497
Panel B. Space Heating Outcomes				
Nighttime Indoor Temperature (°C)				
Treatment	2.22***	1.92***	1.80***	1.78***
	(0.53)	(0.51)	(0.46)	(0.47)
Num.Obs.	1242	1242	950	950
Rooms with Regular Heating				
Treatment	1.67***	1.42***	1.36***	1.38***
	(0.25)	(0.22)	(0.22)	(0.18)
Room Average Heating Duration (hours·room^{-1})				
Treatment	4.16***	3.37***	3.17***	3.17***
	(0.57)	(0.52)	(0.54)	(0.50)
Num.Obs.	2,677	2,677	2,486	2,486
Std.Errors	by: Village	by: Village	by: Village	by: Village
FE: T_Timing	✓			
FE: year	✓	✓	✓	✓
FE: village		✓		
FE: household			✓	✓
Controls:				✓

The increase in the number of heated rooms and room average heating duration means an increase in the total number of hours the house is heated. As illustrated in Figure 3.3a, these enhancements in space heating could be attributed to the expansion of hot water radiator systems. Firstly, the policy has significantly boosted the adoption of hot water radiators. Households that previously relied on spot heating practices, such as coal stoves, wood kangs, and mobile electric heaters, and did not have hot water radiators, underwent installations facilitated by the policy. For example, in Huairou district, the government subsidized radiator installations at an approximate cost of 2,000 RMB (Huairou District People's Government, 2020). As shown in Figure 3.3b, whereas less than 80% of sample households had radiator systems at baseline, about 95% of treated households were equipped with them following the policy's implementation. Secondly, households that already had radiators paired with coal stoves at baseline were promoted to expand their radiator systems to qualify for more powerful, subsidized heat pumps. Specifically, households with a heating area of less than 120 m^2 were eligible for subsidies that covered 5 horsepower heating pumps. However, those requiring more powerful pumps needed to cover the additional cost difference. Conversely, households with more than 120 m^2 were eligible to receive 6 horsepower heating pumps. To meet these requirements, some households chose to increase their heated areas by installing radiators in additional rooms, thus qualifying for the more powerful heating solutions. It is important to note that this occurred after a village had been decided to implement the *Clean Heating Policy.* Consequently, any space heating outcomes related to the expansion of radiator use are still influenced by the policy and are thus included in the overall average treatment effect.



(a) Room heating duration

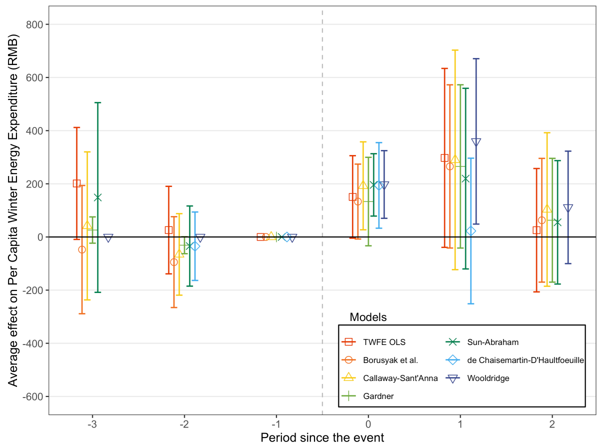
(b) Popularity of the central water radiator

Figure 3.3: Explanation of the treatment effects on space heating outcomes. Bars in Figure 3.3a show the composition of total house heating duration. Colors of the bars show the contributions of different heating practices. The absence of data in the "After" category of the left plot is attributed to the fact that post-treatment measurements are not applicable to the untreated group. Bars in Figure 3.3b show the share of households with water radiator system in different treatment groups and survey years. The single bar in wave 1 is due to no village under treatment of the *Clean Heating Policy* in baseline 2018.

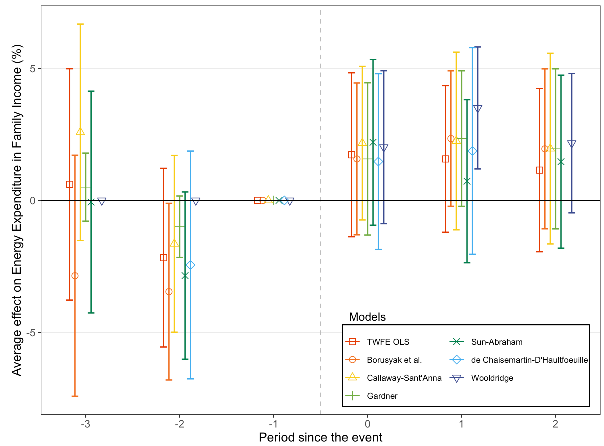
Overall, our findings suggest that while the *Clean Heating Policy* may slightly increase household winter energy expenditures, it significantly improves space heating. Economically, cleaner heating raises households' energy costs and the proportion of income spent on energy, potentially exacerbating energy poverty. However, from a space heating perspective, improvements in indoor temperatures, the number of rooms heated, and the average heating duration indicate a substantial alleviation of energy poverty. To further explore the trade-off between economic and space heating outcomes, we compared the before-and-after differences of households in the treatment group. As shown in Figure B.4 in Appendix B.5, the majority of treated households fall into the quadrant of increased expenditure but improved space heating. This observation suggests a general willingness among households to allocate more of their budget to energy if it results in better fulfillment of their energy needs. Field interviews support this finding, with most households involved in the intervention stating that the increase in fuel costs was acceptable in exchange for significant improvements in heating quality, room cleanliness, time savings, and overall indoor comfort. These insights challenge the sufficiency of purely economic indicators for assessing energy poverty and underscore the importance of incorporating measures that reflect the actual satisfaction of energy needs when evaluating such programs.

3.4.3 Dynamic treatment effects

The dynamic treatment effects of the *Clean Heating Policy* on winter energy expenditure and its share in family income are depicted in Figure 3.4. While the key assumption of our identification strategy, the parallel trend assumption, cannot be directly verified for the post-treatment period, the pre-treatment estimations from the event study, which are both minimal and statistically insignificant at the 5% level, support the validity of this assumption (Rambachan & Roth, 2019). For the post-treatment period, the policy triggers an immediate increase in winter energy expenditure, with these effects persisting over time. All estimators, including traditional TWFE and newer heterogeneous DiD estimators, provide relatively consistent estimations of the dynamic treatment effects after the policy's implementation (starting at period 0). The results for the post-treatment periods show that the policy led to an increase in winter energy expenditure of over 300 RMB in the year of treatment and the subsequent year. However, two years after the implementation of the policy, the treatment effects significantly reduce to approximately 100 RMB. These temporal trends in winter energy expenditure impacts are somewhat mirrored in the changes in the share of expenditure in income. Yet, due to relatively minor fluctuations in winter energy expenditures, the variations in share impacts are not especially pronounced. This reduction in winter energy expenditure is not due to a decrease in energy use by treated households; rather, it is likely attributable to the effects of subsidies on electricity tariffs provided by the policy.



(a) Winter energy expenditure



(b) Share of expenditure in family income

Figure 3.4: Dynamic treatment effects on economic outcomes: winter energy expenditure and its share in family income. Event-study plots constructed using seven different estimators: a dynamic version of the TWFE model, Equation 3.2, estimated using OLS (in red with square markers); Borusyak et al. (2021) (in orange with circle markers); Callaway and Sant'Anna (2021) (in yellow with triangle markers); (Gardner, 2022) (in light green with line markers); Sun and Abraham (2021)(in dark green with cross markers); De Chaisemartin and d'Haultfoeuille (2020)(in light blue with diamond markers); and Wooldridge (2021) (in dark blue with inverted triangle markers). The outcome variable in Figure 3.4a and Figure 3.4b is per capita winter energy expenditure and share of winter energy expenditure in family income, respectively. The x-axis is the relative time between survey year and the year when the *Clean Heating Policy* firstly implemented in a village. Unlike other estimators, we specified the "never treated" units as the control group in Sun and Abraham (2021) estimators. For the De Chaisemartin and d'Haultfoeuille (2020) estimator, we estimate only one pre-treatment and one post-treatment due to the way it defines the maximum number of placebo and dynamic effects. The Wooldridge (2021) estimators mechanically set the pre-treatment effects to zero. Standard errors are clustered at the village level.

In the winter of 2021–2022, two years after early-treated households joined the intervention, the COVID-19 pandemic significantly increased the amount of time families spent at home due to strict government-imposed quarantine measures. This surge in home occupancy led to higher winter electricity bills for all households, attributable to increased usage of lighting, entertainment devices, and additional heating appliances such as portable electric heaters and electric blankets. Figure 3.5 shows that both untreated and treated households saw a notable rise in their winter electricity expenditures in 2021. However, the increase was less pronounced in treated households, who benefited from the policy's electricity tariff subsidies that were active between 8 pm and 8 am during the heating season. These subsidies also inadvertently covered the cost of electricity used for non-heating purposes during the subsidized hours. Despite the government's efforts to more accurately target these subsidies specifically towards space heating — such as the installation of a second electricity meter — over 80% of the sampled households continued to enjoy the reduced tariffs for various uses by the end of the study period.

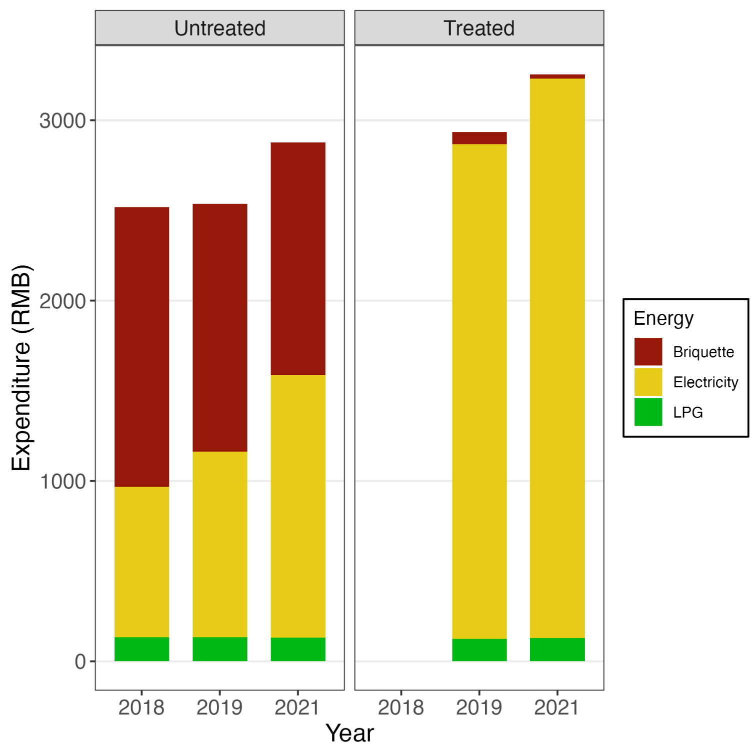
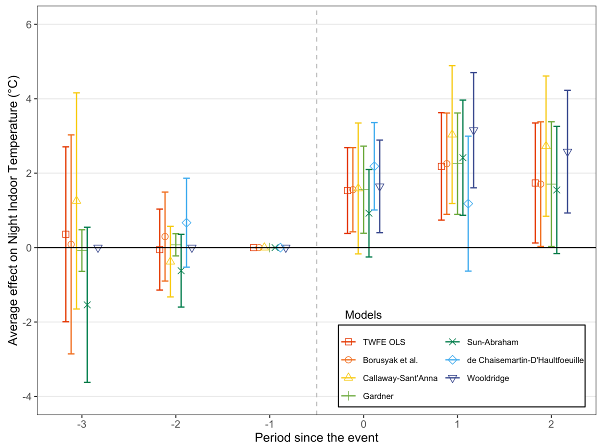
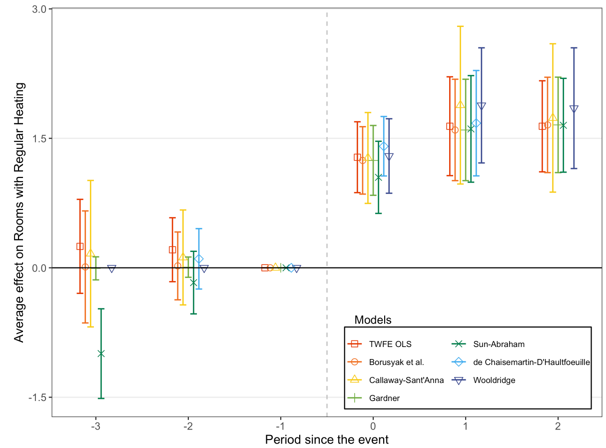


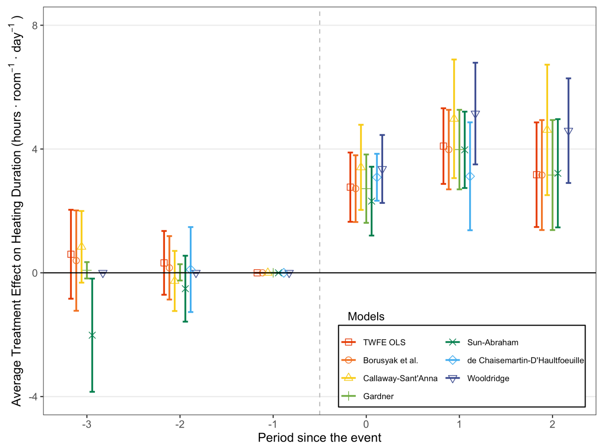
Figure 3.5: Winter energy expenditures of treated and untreated households in different years. The color of the bar indicates the common types of energy sources including briquettes, electricity, and LPG. The right plot contains only two bars since there is no village under treatment of the *Clean Heating Policy* in baseline 2018.



(a) Nighttime indoor temperature



(b) Rooms with regular heating



(c) Room average heating duration

Figure 3.6: Dynamic treatment effects on space heating outcomes. This figure shows the event study results on (a) indoor temperature, (b) rooms with regular heating, and (c) room average heating duration. See the notes of Figure 3.4 for details.

Figure 3.6 presents the results of the event study on space heating outcomes. The *Clean Heating Policy* has a positive impact on rural household indoor temperature, rooms with regular heating, and average heating duration once the households entered the policy. These benefits have proven to be sustained, with positive impacts observable up to two years after the intervention. Additionally, most of the estimated coefficients in the pre-treatment period are small and not statistically different from zero. Given that the trends of outcomes in the treatment and control groups are similar prior to the *Clean Heating Policy*, this supports the validity of our identification assumption post-treatment, thereby enhancing the credibility of our findings.

The consistent positive impact on indoor temperature within the *Clean Heating Policy* is possibly bolstered by the government's guidance on temperature settings for heating pumps. Official guidelines recommend that the water temperature of end radiators should be set within the range of 35–45°C. Considering potential barriers to adopting new technologies, such as the age and education level of the mountain population, households generally comply with government recommendations regarding temperature settings. They maintain a consistent temperature across the years rather than frequently adjusting the settings of their heat pumps in response to outdoor temperature changes. Additionally, the government employs a cloud-based platform to remotely monitor the operating conditions of heat pumps, enhancing reliability and preventing operational failures (L. Zhang et al., 2022). This systematic approach helps ensure efficient heating and minimizes the risk of technical issues, contributing to the sustained effectiveness of the policy.

3.4.4 Heterogeneity analysis

In the preceding section, we discussed the average treatment effects of the *Clean Heating Policy* on winter energy expenditure and space heating. Nonetheless, it is crucial to acknowledge that the policy's impact may vary across households with diverse socioeconomic statuses and heating infrastructure. To acquire a more nuanced understanding of the policy's impact, this section examines the heterogeneous treatment effects on households with different characteristics. We specifically investigate how the policy's impacts vary among households living at different village altitudes, with varying heating infrastructure, and different wealth statuses at baseline.

By village altitude. In mountainous regions, households face distinct financial challenges under the *Clean Heating Policy* due to increased heating requirements and fewer livelihood opportunities. This poses a significant concern for the government's implementation of the policy in mountainous regions. The results from Equation 3.3 displayed in

Panel A of Table 3.3 reveal how the treatment effects vary by village altitude. The coefficients of the interaction term between the treatment status and village altitude (Treatment $\times$ (altitude $\div$ 100m)) demonstrate differential impacts of households residing in villages at different altitudes. Although there is no statistically significant difference in the impacts on our space heating metrics, we find strong evidence of the heterogeneous treatment effects on expenditures and share of income spent. It is noteworthy that for every 100 meters of elevation gain in the village, the impacts of the *Clean Heating Policy* on per capita winter energy expenditure and share in income increase by 208 RMB and 1.5%, respectively. Considering the altitude range within our sample from 118m to 680m, and assuming a linear response function, this results in a substantial disparity of nearly 1,165 RMB in winter energy costs between households in the lowest and highest villages. Extending this model, we estimate that households in Beijing's highest-altitude villages at 1,400 meters could face winter energy costs about 2,900 RMB higher than those in the plains. These findings suggest a cautious approach in promoting the *Clean Heating Policy* in mountainous regions and the notably extreme cold winter provinces of the northwestern and northeast (Meng et al., 2023; Zhou et al., 2022).

By heating infrastructure. Transitioning from point heating methods like coal stoves and mobile electric heaters to hot water radiator systems represents a significant shift in residential heating practices. Panel B in Table 3.3 displays the heterogeneous treatment effects for households based on whether they have a water radiator system in the baseline. The significant magnitude of the coefficients on the interaction term, Treatment $\times$ (Radiator $= 1$), indicate that the economic and space heating outcomes are substantially more pronounced for households that did not have a radiator system in the baseline. For households without hot water radiators at baseline, the impact of the *Clean Heating Policy* on winter energy expenditure and its share in income, as well as on indoor temperatures, is over five times greater than that observed in households with radiators. Furthermore, the notable differences in average heating duration between households with and without radiators at baseline underline the significant benefits of radiator systems in extending heating duration, reinforcing the findings discussed earlier.

By wealth status. For wealthier households, the policy may simply provide a gentle push towards completing the transition to cleaner heating, whereas for poorer households, it may pose significant financial challenges and force them to sacrifice adequate space heating. To provide a comprehensive view of the long-term stable socioeconomic status of the sample households, we utilized principal component analysis (PCA) to combine various asset profiles (such as land, vehicles, appliances, and housing) from the baseline into a wealth index (detailed in our prior study X. Li et al. (2022)). This wealth index serves as a robust indicator of household socioeconomic status, as evidenced by its strong correlation with a variety of socioeconomic characteristics, including income and consumption, as Figure B.5 demonstrated in Appendix B.8 .

Panel C in Table 3.3 illustrates the heterogeneous treatment effects of the policy on households within subgroups of the wealth index. While no statistically significant differences in energy poverty indicators are observed at the 5% significance level among households in the top, middle, and bottom wealth index groups, it is noteworthy that households in the lowest third of the wealth index experience more pronounced economic impacts compared to the other two groups. One reassuring indication is that despite the greater economic impacts, as the coefficients of $\text{Treat}_{\text{reference}}$ indicate, the *Clean Heating Policy* enhanced the space heating for households in the lowest wealth group. Conversely, the average heating duration of households in the top third of the wealth index exhibits a smaller increase compared to the other two groups. This variation may still be attributed to the level of radiator penetration across different wealth index groups, as depicted in Figure B.6 in the appendix, where the wealth index demonstrates a positive correlation with the penetration of hot water radiator systems in baseline.

Table 3.3: Heterogeneous treatment effect of different subgroups of households. This table provides estimates of coefficient β derived from Equation 3.3. The $\text{Treatment}_{\text{reference}}$ estimations represent the treatment effects on the reference group, while estimations involving the interaction term between treatment and "moderators" C_i show differences between these other groups and the reference group. The $\text{Treatment}_{\text{reference}}$ in Panel A is the treatment effects at mean altitude ($C_i = \overline{C}$). Standard errors are clustered at the village level. * p < 0.1, ** p < 0.05, *** p <0.01.

	Heterogeneous treatment effects on subgroups				
Dep. var.:	Exp	Share	Temp	Rooms	Duration
Panel A. Village altitude					
$\text{Treatment}_{\text{reference}}$	195.36**	2.09*	1.79***	1.38***	3.17***
	(80.21)	(1.09)	(0.46)	(0.18)	(0.50)
Treatment × (altitude ÷ 100m)	207.89**	1.52**	0.45	-0.04	0.01
	(90.70)	(0.74)	(0.44)	(0.19)	(0.57)
Observations	2497	2497	950	2486	2486
Panel B. Radiator in baseline					
$\text{Treatment}_{\text{reference}}$	574.19***	6.85***	6.18***	2.65***	7.02***
	(147.32)	(2.43)	(1.56)	(0.35)	(0.75)
Treatment × (Radiator = 1)	-488.30***	-6.04***	-5.09***	-1.58***	-4.79***
	(129.95)	(2.15)	(1.60)	(0.36)	(0.91)
Observations	2497	2497	950	2486	2486
Panel C. Wealth group					
$\text{Treatment}_{\text{reference}}$	317.40**	2.99	1.33	1.34***	3.29***
	(124.41)	(1.82)	(0.84)	(0.22)	(0.69)
Treatment × Middle 1/3 Wealth	-197.06	-1.79	0.37	-0.11	0.14
	(137.80)	(1.90)	(0.81)	(0.25)	(0.75)
Treatment × Top 1/3 Wealth	-202.18*	-1.07	1.06	0.26	-0.49
	(118.26)	(2.09)	(1.12)	(0.28)	(0.61)
Observations	2,495	2,495	950	2,484	2,484
Std.Errors	by: Village	by: Village	by: Village	by: Village	by: Village
FE: household	✓	✓	✓	✓	✓
FE: year	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓

3.4.5 Robustness check

In this section, we conduct a robustness check of our estimation through placebo tests and discuss the uncertainty of some of the self-reported data.

3.4.5.1 Placebo test

Placebo tests provide support for the energy expenditure (or space heating) effects we estimated, indicating that they are indeed caused by the treatment, the *Clean Heating Policy*, rather than unrelated factors. We perform placebo tests in two ways: (1) on variables that should not be affected by the implementation of the policy and (2) on a "fake" treatment status. To assess the impact of the "fake" treatment status, we employed two distinct approaches: in-time and in-space placebo tests.

We initially conducted the baseline regression on three variables that should not be impacted by the *Clean Heating Policy*: the age of our health survey participants, the age at which current smokers began smoking, and the household farmland area.[4] Table 3.4 presents the results from a placebo test concerning three "irrelevant" variables. The treatment effects of the *Clean Heating Policy* on these variables are very close to 0 and not statistically significant at the 5% level. These findings strengthen the argument that the observed positive impacts on economic and space heating outcomes are not likely due to Type I errors.

[4] In follow-up surveys, the health survey participant within a household may change if the original participant is unavailable.

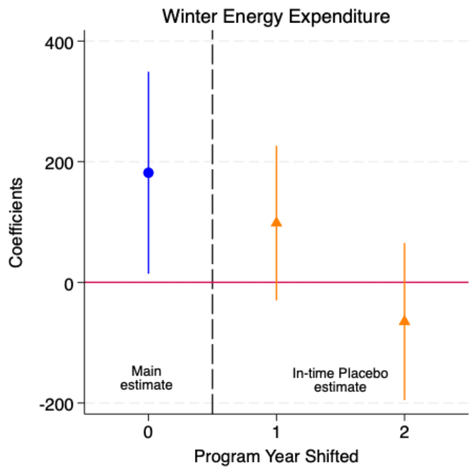
Table 3.4: Placebo test: treatment effects on "irrelevant" variables. This table presents estimates of the coefficient β from Equation 3.1, using outcome variables that should not be affected by the *Clean Heating Policy.* These include the age of the health participants, the age at which current smokers started smoking, and the area of farmland. Standard errors, shown in parentheses, are clustered at the village level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Placebo test: on "irrelevant" variables		
Dep. var.:	Age	Smoke Age	Farmland
Treatment	-0.03	0.10	0.06
	(0.21)	(0.62)	(0.11)
Num.Obs.	2,493	588	2,491
Std.Errors	by: Village	by: Village	by: Village
FE: household	✓	✓	✓
FE: year	✓	✓	✓
Controls	✓	✓	✓

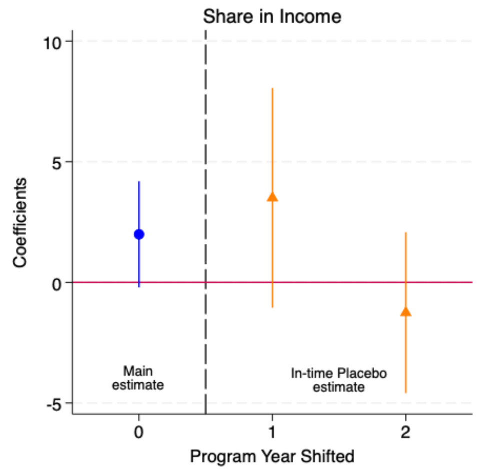
We conducted an in-time placebo test to assess the robustness of our baseline estimations. For this test, we constructed a "fake" treatment status by advancing the actual treatment timing of the *Clean Heating Policy* by one or two years for the treated households. This placebo test, carried out on a subsample that excludes all actual treated observations, serves as a pre-trend test, providing additional support for the parallel trends assumption beyond the pre-treatment event study results discussed in Section 3.4.3 (Huang & Liu, 2023). Figure 3.7 shows the results of this test. The x-axis represents the years by which the *Clean Heating Policy* was hypothetically advanced, with 0 indicating the actual treatment year. The coefficients and 95% confidence intervals displayed in Figure 3.7 reveal no statistically significant impacts from the placebo treatments across all five outcomes of interest, further substantiating the validity of our identification strategy.

Our in-space placebo test involved randomly selecting individuals from the sample to serve as "fake treatment units," with no replacement. We then conducted DiD estimations to determine the placebo effect. This process was repeated 500 times using Monte Carlo simulations, facilitated by the newly developed STATA command "didplacebo" (Chen et al., 2023). Figure 3.8 displays the results with gray bars and orange lines representing the distribution and kernel density of the in-space placebo estimates across all five outcomes of interest, based on 500 simulations. The actual estimations from Table 3.2 column 4 are marked by red vertical lines.

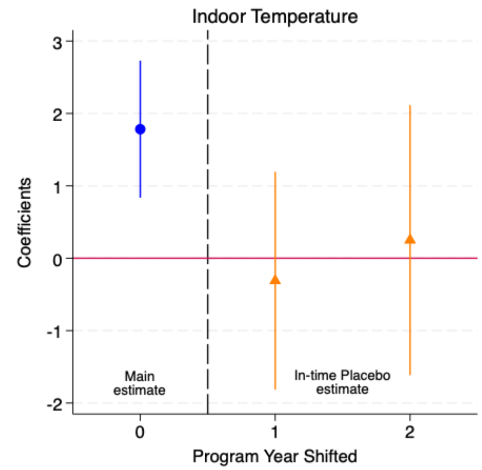
The distributions of the 500 in-space placebo estimates approximate a standard normal distribution. Notably, for the three space heating outcomes — indoor temperature, number of heated rooms, and average heating duration — the absolute values of the placebo estimated coefficients from the 500 simulations are consistently smaller than our main estimations. For per capita winter energy expenditure, the main estimation lies in the right tail of the placebo distribution, with only 1% of the placebo estimates exceeding it. Regarding the share of winter energy expenditure in family income, which was not statistically significant at the 5% level in our main estimation, there are 7% of the placebo estimators surpass the main estimation.



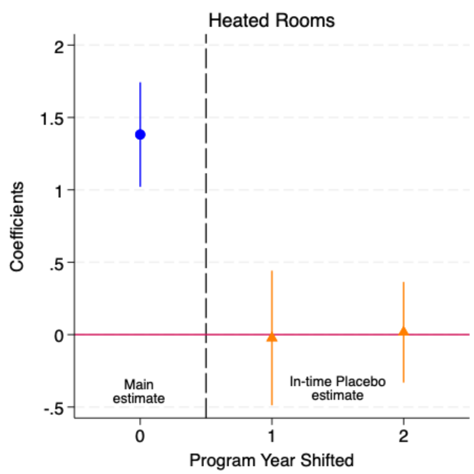
(a) Winter energy expenditure



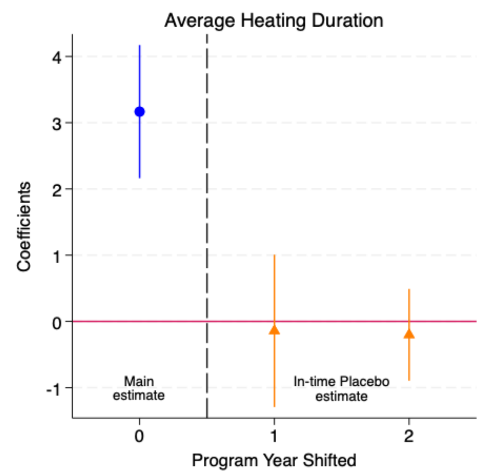
(b) Share in income



(c) Nighttime indoor temperature

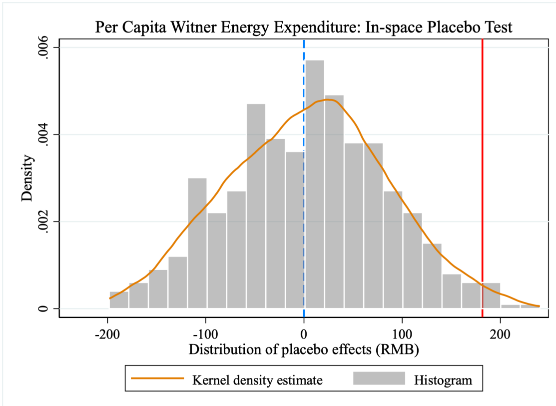


(d) Rooms with regular heating

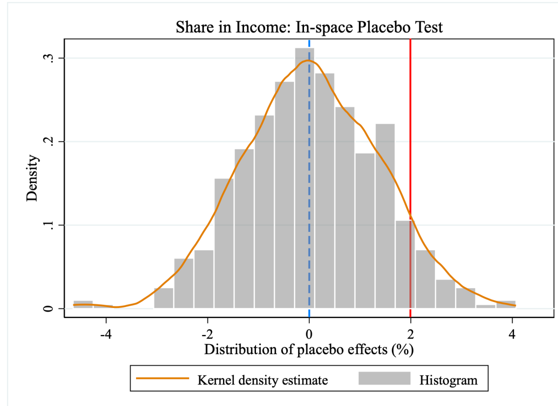


(e) Average heating duration

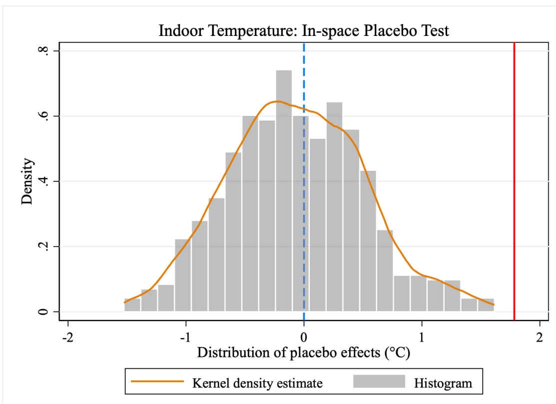
Figure 3.7: In-time placebo test of economic and space heating outcomes. This figure shows the in-time placebo test results by shifting the actual treatment timing by one or two years in advance. The x-axis indicates the years of the treatment timing shifted with 0 represent the treatment year in reality. The blue line with the circle markers are the main estimations while the orange lines with the triangle markers are the in-time placebo estimations. The intervals are the 95 percent confidence intervals based on standard errors clustered at the village level.



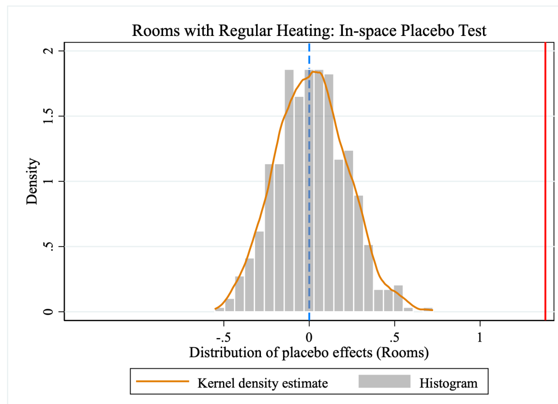
(a) Winter energy expenditure



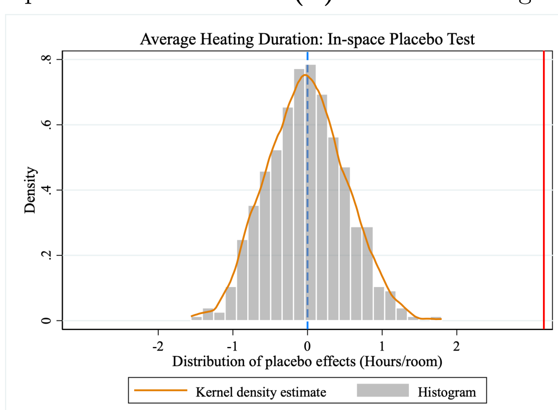
(b) Share in income



(c) Nighttime indoor temperature



(d) Rooms with regular heating



(e) Average heating duration

Figure 3.8: In-space placebo test of economic and space heating outcomes. This figure shows the in-space placebo test results by randomly determining the treatment status across households. The gray bars and orange lines illustrate the distribution of 500-time Monte Carlo analysis on estimation of Equation 3.1. The red vertical lines represent the main estimation results based on the treatment status in reality.

3.4.5.2 Robustness of self-reported data

The reliability of self-reported income data from surveys is a perennial concern, especially when derived from a single question. This issue primarily arises from two factors: first, the imperfect response rate, as respondents frequently hesitate to disclose income information due to privacy concerns; and second, the potential for response bias, which may be influenced by the comprehensiveness of income sources considered and the respondent's ability to accurately report income figures (Micklewright & Schnepf, 2010). These reliability challenges can significantly skew the estimation of our outcome variable, the share of winter energy expenditure in household income.

To enhance the reliability of self-reported income data, our survey design broke down family annual income into distinct categories: wages, agricultural income, business revenues, remittances, and government subsidies. This segmentation reflected the diverse income sources typical within our sample population. The components were then aggregated to compute the total annual household income. This method reduced the sensitivity often associated with direct inquiries about total income and helped respondents more accurately account for various income streams, simplifying the reporting process and promoting consistency in measurement across participants.

Despite these improvements, 0.3% of the observations reported a total household income of zero, which could indicate a refusal to disclose income details. Additionally, 4.5% of the observations recorded a per capita annual income below 3,000 RMB, a figure that seems unrealistically low given the coverage of China's social security system, including basic pension insurance for urban and rural residents and rural minimum living security funds. Consequently, we applied a bottom-coding approach for households reporting incomes below this threshold, setting 3,000 RMB as the minimum per capita income. This decision was informed by 2017 data indicating that annual per capita food consumption in rural Beijing amounted to 4,653 RMB, coupled with the fact that our sample districts are among the economically weaker regions in Beijing. Based on the income sources and consumption levels observed in the sample villages, a threshold of 3,000 RMB represents a reasonable estimate for minimum subsistence income.

To verify the robustness of our processed self-reported income data, we conducted the baseline regression analysis on the share of winter energy expenditure in household income using three sub-samples. These sub-samples systematically excluded the bottom and top 2.5%, 5%, and 10% of extreme per capita income observations, respectively. The results, detailed in Table 3.5, show consistent treatment effect estimations on share of winter energy expenditure in family income across all sub-samples compared to the baseline. This consistency suggests that extreme income values have a minimal impact on our outcome variable, affirming the reliability of our findings despite potential variations in reported income levels.

Table 3.5: Robustness of self-reported income data: treatment effects on share of winter energy expenditure based on subsample. This table presents estimates of coefficient β from Equation 3.1 on subsample with the share of winter energy expenditure in income as the outcome variables. We determine the subsets of households by removing households with 2.5%, 5%, and 10% income extremes. Standard errors, shown in parentheses, are clustered at the village level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Dep. var.:	Share of Winter Energy Expenditure in Income(%)		
Subsamples	95% sample	90% sample	80% sample
Treatment	1.71*	1.87*	1.73*
	(0.92)	(0.95)	(0.88)
Num.Obs.	2,233	2,144	1,819
Std.Errors	by: Village	by: Village	by: Village
FE: household	✓	✓	✓
FE: year	✓	✓	✓
Controls	✓	✓	✓

Another source of uncertainty in our primary findings arises from the method used to determine winter energy expenditures. Although both household coal briquette consumption and electricity expenditure were self-reported, the uncertainty in coal expenditure is significantly lower than that of electricity bill. This is because households ordered their winter heating coal briquettes in advance through the *Reduce and Substitute Coal Program* by submitting orders to the village committee, which were then coordinated with the district government. Additionally, each household received a subsidized coal purchase quota based on household size, ensuring that they had a clear understanding of their coal consumption during the heating season. Furthermore, within the same township, households purchased coal briquettes at a standardized price, minimizing the likelihood of uncertainty or measurement error in self-reported winter coal expenditures.

Regrading the winter electricity bill, our survey, conducted early each winter, requires households that have recently transitioned to the new heating technology to estimate their upcoming season's electricity bills. Figure 3.9 shows the disparity between self-estimated winter electricity bills and actual bills, the latter retrieved via the "Wangshangguowang (网上国网)" mobile application. Not all households have smartphones or use this app, so our data includes actual winter electricity bills from only about forty households.

Both untreated and treated households tend to misjudge their winter electricity expenses, but treated households are particularly prone to underestimating them. This tendency suggests that our calculations of the average treatment effects on winter energy expenditure might be conservative, acting as a lower-bound estimate rather than an overestimation.

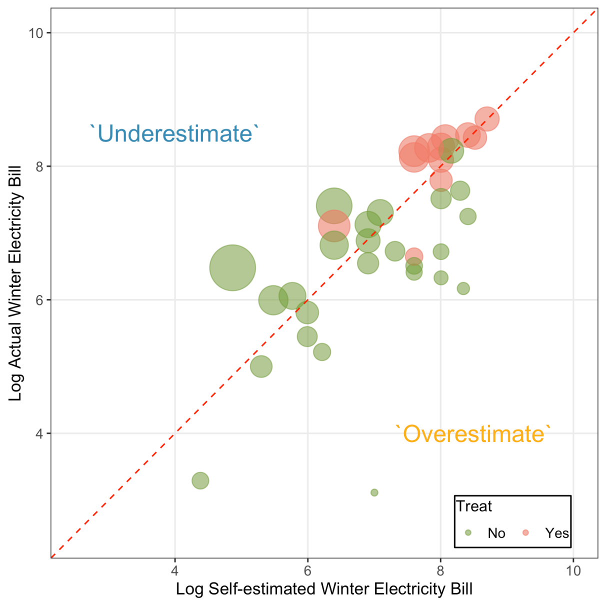


Figure 3.9: Robustness of self-estimated winter electricity bill. This figure illustrates the correlation between self-estimated winter electricity bills and the actual bills collected through households' "Wangshangguowang" application. The color of the scatter points represents the treatment status, while the size of the points represents the ratio between the actual and self-estimated winter electricity bills. The 45-degree dotted line indicates where the estimated electricity bill equals the actual electricity bill.

3.4.5.3 Heterogeneity-robust DiD estimators

Although we have thoroughly analyzed the dynamic treatment effects using various heterogeneity-robust DiD estimators in Section 3.4.3, this section further examines the robustness of the TWFE estimator on average treatment impacts. The consistent estimation of post-treatment dynamic effects, as illustrated in Figure 3.4 and Figure 3.6, suggests that the estimates of average treatment effects, obtained after weighted averaging, also remain consistent. Figure B.2 in the appendix displays these average treatment effects from various DiD estimators.

The Bacon Decomposition, detailed in Figure B.7 in the appendix, clarifies this consistency. Operating within a staggered DiD setting — where no sample village is covered by the *Clean Heating Policy* at baseline and 60% of sample villages remain "never treated" throughout the study — the weighted average TWFE estimator is primarily influenced by the "good" 2×2 estimators (i.e., treated versus never treated), which contribute about 80% to the TWFE average treatment effects. In contrast, the problematic "later treated versus early treated" estimator accounts for only about 10% of the main TWFE estimator. As shown in Figure B.7, there are only minor discrepancies among the decomposed 2×2 estimators, suggesting that the potential biases introduced by staggered treatment are minimal and do not significantly threaten our main estimation results.

3.5 Discussion

In this section, we further discuss and perform some robustness checks on our main findings.

3.5.1 Potential financial challenges under different subsidy scenarios

All of our findings thus far regarding the economic and space heating impacts have relied on the "triple subsidies" provided by the municipality-district-town governments in Beijing. Given the positive externalities, including enhanced ambient air quality, heightened energy efficiency for the broader society, and diminished greenhouse gas emissions, governmental subsidies for cleaner heating hold considerable potential for substantial social benefits (Berkouwer & Dean, 2023). In the 2020–2021 heating season, the Beijing municipality-district governments provided a tariff subsidy of 0.73 billion RMB for the *Clean Heating Policy* (Beijing Association for Sustainable Development, 2021). Even in 2023, a decade after the inception of the *Clean Heating Policy* in rural Beijing, electricity tariff subsidies persist, with the government additionally unveiling a subsidy policy for households proactively replacing equipment upon reaching the end of its lifespan (The People's Governemnt of Beijing Municipality, 2023). However, the question about sustainability of such financial support endeavors raises questions, with households expressing apprehensions during interviews regarding the potential dwindling or cessation of subsidies.

Given the potential uncertainty surrounding the long-term sustainability of the *Clean Heating Policy*, it is crucial to assess its economic implications under various subsidy scenarios. Figure B.3 in the appendix outlines three scenarios that consider different levels of subsidy cancellation: Scenario 1 involves the cancellation of electricity tariff subsidies from one level of government, either town or district level); Scenario 2 includes the combined cancellation of tariff subsidies from both town and district governments; Scenario 3 entails the additional cancellation of nighttime valley tariff subsidies, requiring households to pay the regular electricity tariff. To assess the economic impact of these scenarios, we simulated electricity costs by adjusting current expenditures according to specific multipliers reflective of each subsidy cancellation scenario.

Table 3.6 presents the estimated economic costs based on these simulations. Even under Scenario 1, the most moderate case where only one tier of government subsidy is withdrawn, energy expenditures increase fivefold compared to the current scenario. This increase translates to an additional cost of approximately 8% of annual household income. In the most extreme case, Scenario 3, where all electricity subsidies are eliminated, per capita winter energy expenditure rises by 3,920 RMB, which equates to 32% of family income. While these simulations do not account for potential adaptive responses, they clearly demonstrate the substantial economic burden that even minor subsidy adjustments could impose on rural households. We earlier noted the combination of increased expenditure coupled with increased quantity of heating at the subsidized prices, suggesting a possibly positive wealth effect from the policy. It seems likely that under such extreme prices as in these Scenarios, the policy would have resulted in both less disposable income and less household heating.

Good thermal insulation performance in housing is crucial for reducing energy consumption, alleviating the financial burden of heating for households, and improving space heating (Yang et al., 2010). Since most rural homes in northern China are self-built and lack uniform construction standards, nearly 80% of rural dwellings do not have insulation measures, resulting in significantly higher per-unit energy consumption compared to urban residences (National Development and Reform Commission, 2017).

During the pilot phase of the *Clean Heating Policy*, government documents indicated that villages that had completed insulation retrofitting would be prioritized for policy implementation. However, during the large-scale implementation phase, despite policy requirements to integrate insulation improvements, we observed that many villages did not complete retrofitting either beforehand or concurrently with the *Clean Heating Policy*. For example, in our sample households, only about 30% had insulated all their walls, and only 20% had completed roof insulation. Thus, our estimated policy impacts reflect conditions where insulation remains inadequate.

If comprehensive insulation retrofitting were conducted, the policy could potentially yield more desirable outcomes. Additionally, for provinces in severely cold regions, even in the absence of the *Clean Heating Policy*, improving housing insulation could help reduce coal consumption while also preparing for future clean heating transitions (Z. Wang et al., 2022).

Table 3.6: A straightforward calculation of the potential financial challenges under subsidy scenarios. This table presents estimates of coefficient β derived from Equation 3.1, with a straightforward calculations of per capita winter energy expenditure and the share of winter energy expenditure to income under different subsidy scenarios as outcome variables. We use "Treatment" (in quotes) to distinguish these hypothetical scenarios from the actual treatment in reality. Standard errors, shown in parentheses, are clustered at the village level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Scenarios:	Current	Scenario 1	Scenario 2	Scenario 3
Panel A. Per capita winter energy expenditure (RMB)				
"Treatment"	181.71**	1145.07***	2108.43***	3919.55***
	(83.31)	(164.46)	(250.10)	(413.49)
Panel B. Share of winter energy expenditure in family income (%)				
"Treatment"	1.99*	9.83***	17.67***	32.41***
	(1.09)	(1.91)	(2.78)	(4.44)
Num.Obs.	2,497	2,497	2,497	2,497
Std.Errors	by: Village	by: Village	by: Village	by: Village
FE: household	✓	✓	✓	✓
FE: year	✓	✓	✓	✓
Controls	✓	✓	✓	✓

3.5.2 Uptake effects of the *Clean Heating Policy*

One minor challenge in defining treatment status arises from a small subset of households in treated villages that delayed new heating equipment installation due to ongoing or planned renovations coinciding with the village-wide *Clean Heating Policy* implementation. Less than 5% of treated village observations exhibited this behavior. We considered such behavior, reflecting individual reactions to the treatment, as part of the treatment effects. In this section, we explored the household-level "uptake" effects instead of the village-level treatment effects reflected in the main results.

We define "uptake" as whether a household adopts new heating technology. Table B.2 in the appendix presents the descriptive statistics for energy poverty outcomes among households in the villages haven been treated by the *Clean Heating Policy* and those who actually have taken up the new heating technology. Using this redefined independent variable, we re-estimate the baseline regression (Equation 3.1). Table 3.7 presents the uptake impacts on economic and space heating indicators. These "uptake" impacts are more significant and larger than the treatment effects, particularly on economic outcomes. Specifically, the adoption of the new heating equipment from the *Clean Heating Policy* resulted in a rise in per capita winter energy expenditure by 226 RMB, equivalent to a 2.7% increase in its share in family income. Both coefficients are statistically significant at the 5% level. Moreover, the uptake impacts on these two outcomes are 24% and 33% higher than the treatment impacts, respectively. Therefore, our main results provide conservative estimations of the impacts of the *Clean Heating Policy* on energy poverty.

Table 3.7: Uptake effects of the *Clean Heating Policy*. This presents estimates of coefficient β from Equation 3.1 with whether a household uptake the new heating equipment from the *Clean Heating Policy* as the independent variable. Distinguished from "treatment", "uptake" requires households to be not only in the treated villages, but also to use clean heating technologies as a means of space heating. Standard errors, shown in parentheses, are clustered at the village level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Dep. var.:	Exp	Share	Temp	Rooms	Duration
Uptake	226**	2.65**	1.80***	1.56***	3.57***
	(88.67)	(1.21)	(0.47)	(0.17)	(0.50)
Num.Obs.	2,497	2,497	950	2,486	2,486
Std.Errors	by: Village	by: Village	by: Village	by: Village	by: Village
FE: household	✓	✓	✓	✓	✓
FE: year	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓

3.6 Conclusion

In this paper, we analyze the effects of the *Clean Heating Policy* in rural northern China, one of the largest household energy interventions globally, on various aspects of energy poverty. Our findings reveal significant and enduring positive impacts on both economic and space heating outcomes among households covered by the *Clean Heating Policy*. In comparison to households in villages still reliant on burning coal briquettes for space heating, those in *Clean Heating Policy* treated villages expend approximately 180 RMB more on per capita winter energy expenditure. Nevertheless, they experience a notable improvement in nighttime indoor temperature by 1.8°C, accompanied by an increase of 1.4 additional rooms with regular heating and an extended average room heating duration by 3 hours per day. This underscores the willingness of individuals to invest more in enhancing their energy services and achieving thermal comfort in their living spaces, when the financial impact of the intervention policy is relatively minor. Furthermore, our results highlight the significance of integrating economic impacts with the level of energy demand satisfaction when evaluating the impacts of intervention programs on household energy poverty.

We also observe heterogeneous treatment effects across village altitude, baseline heating infrastructure, and household socioeconomic status. While there are no statistically significant differences in space heating impacts, households residing in high-altitude villages incur higher expenditures on winter energy use. Furthermore, although households lacking hot water radiators before the treatment experience considerable financial strain, they experience much better heating improvement. The dissemination of water radiator systems also partially accounts for the finding that households in lower wealth index groups experience more significant impacts from the policy.

Our straightforward calculation indicates that the observed trend of "paying slightly more for significantly improved heating comfort" may heavily rely on generous subsidies from the Beijing government. This implies that if the positive effects of the *Clean Heating Policy* on energy transition, health, and air quality improvements are to be sustained, high government subsidies may need to remain in place for a considerable period. Whether households can develop a long-term habit of using clean energy and gradually reduce their reliance on government subsidies is a key issue for future policy considerations. This analysis further illustrates that with appropriately designed incentives, households are willing to increase their energy expenditure to access higher levels of energy services. Consequently, the energy transition not only benefits individual households but also fosters a win-win scenario for society by enhancing environmental, health, and economic outcomes from the individuals' positive externality. Our findings carry significant policy implications for the ongoing *Clean Heating Policy* in rural China, as well as for other countries seeking to promote household energy transition through heating interventions.

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Bridging text

The findings presented in **Chapter 3** help alleviate some concerns regarding the impact of the *Clean Heating Policy* on vulnerable rural households, particularly in terms of energy poverty. The results indicate that households have experienced significant improvements in space heating with minimal financial burden. However, given that this transition was mandatory, it raises questions about how households perceive these outcomes.

Beyond economic impacts, the energy transition influences various important domains of life. In addition to the improvements in indoor temperatures discussed in the previous chapter, the use of clean energy can significantly enhance the living environment. This includes reductions in indoor air pollution, increased cleanliness within the home, and improved outdoor air quality. Moreover, improvements in temperature and air quality through energy transition offer substantial health benefits, such as reducing the risk of cardiovascular and respiratory diseases. Particularly for rural households in northern China, the energy transition can significantly reduce the frequent incidents of carbon monoxide poisoning caused by burning solid fuels for heating in winter. Furthermore, the energy transition can markedly decrease the time households spend collecting and using solid fuels, thereby providing greater convenience in energy usage. Consequently, the impact of the energy transition on well-being is multifaceted and significant.

Chapter 4 aims to assess how households experience the *Clean Heating Policy*'s impact on overall quality of life. We will evaluate the impact of the *Clean Heating Policy* on household subjective well-being and explore the underlying mechanisms of this influence. In this chapter, we focus on households participating in the *Clean Heating Policy* as the primary subjects for policy evaluation, with their self-assessment of well-being serving as the study's main objective. This approach offers a new perspective for evaluating the impact of current household energy transition projects.

Chapter 4

Household energy transition and subjective well-being: A difference-in-differences estimate of outcomes in rural northern China

This chapter is being prepared for submission to a journal as: Xiang Zhang, Christopher P. Barrington-Leigh, Brian E. Robinson et al., "Household Energy Transition and Subjective Well-being: A Difference-in-differences Estimate of Outcomes in Rural northern China."

Abstract

Transitioning households from solid fuels to modern energy sources is crucial for improving living conditions, health outcomes, and achieving sustainable energy futures. However, there is a noticeable gap in the literature regarding how this energy transition affects the quality of life from the perspective of affected households. This study leverages a natural experiment — the *Clean Heating Policy* in rural northern China — to assess the impact of household energy transition on subjective self-reports of overall quality of life. Utilizing difference-in-differences estimations on panel data from a survey of over 1,200 rural households conducted between 2018 and 2022 in Beijing, we find that the transition increases average life satisfaction by 0.36 on a 0 to 10 scale (95% confidence interval: 0.09–0.63). The impacts on satisfaction with living conditions and income are less pronounced. Additionally, our results suggest that younger, wealthier households and those in poorer health experience more substantial improvements in life satisfaction. These improvements are likely due to the ease and safety of the new energy sources and the enhanced comfort provided by better heating solutions.

4.1 Introduction

As of 2023, a significant portion of the impoverished population in developing countries remains afflicted by energy poverty, defined as "the lack of access to modern energy services and products" (Kumar, 2020). This challenge predominantly affects over 745 million people in sub-Saharan Africa and developing Asia, who still lack access to electricity (IEA, 2023). Additionally, approximately one-third of the global population relies on burning solid fuels for cooking and space heating (IEA et al., 2022).

Adequate domestic energy for cooking, lighting, and heating is essential to enhancing people's quality of life. Per capita energy consumption is strongly correlated with various quality of life indices, such as life expectancy and gross national income (Pasten & Santamarina, 2012). According to Modi et al. (2005), individuals require at least 50 kilograms of oil equivalent per year to satisfy the most fundamental energy needs for cooking and lighting.

Beyond merely fulfilling basic needs with sufficient quantity, the quality of domestic energy services plays a crucial role in enhancing the overall quality of life. Modern energy sources such as electricity and liquefied petroleum gas (LPG) are generally preferred by households due to their superior fuel efficiency (Malakar & Day, 2020). These modern energy sources offer numerous benefits, including reduced emissions of air pollutants and greenhouse gases, which enhance human health and advance the rights of women and children (Floess et al., 2023; Rehfuess & World Health Organization, 2006; Shi et al., 2022; Tibrewal & Venkataraman, 2021). Transitioning households from solid fuels to modern energy sources is thus considered a critical step toward sustainable development (IEA, 2023; Kaygusuz, 2007, 2012). This shift aligns with the United Nations' Sustainable Development Goal 7 (SDG 7), which emphasizes the importance of ensuring accessible, reliable, and affordable modern energy for all by 2030 as part of its broader 2030 Agenda (Villavicencio Calzadilla & Mauger, 2018).

Despite its critical importance, progress in the global household energy transition has been slow. The challenges of achieving SDG 7 by 2030 have been exacerbated by the COVID-19 pandemic and rising energy prices since mid-2021, particularly in vulnerable developing countries (IEA et al., 2023). According to the Paris Agreement evaluation report, the rate of behavioral change toward a clean energy transition has been deemed “not on track” (IEA, 2023). Targeted interventions may be necessary to accelerate progress (Pachauri et al., 2021). Several household energy interventions have shown significant impact, such as the Clean Cooking Alliance (CCA) (Clean Cooking Alliance, 2021; K. R. Smith, 2010), Ecuador’s National Efficient Cooking Program (NECP) (Davi-Arderius et al., 2023; Martínez et al., 2017), and Bangladesh’s Solar Home Systems Program (Cabraal et al., 2021). These programs have significantly promoted universal electricity access and the adoption of clean cooking technologies.

In the preceding text, we have used the terms “well-being” and “quality of life” interchangeably when describing the relationship between domestic energy use and people’s life. Well-being typically refers to a global evaluation of a person’s life (Diener, 2009). Although the definition and conceptualization of well-being is sometimes left ambiguous, it is increasingly recognized as a central goal of development, as highlighted by the United Nations Human Development Index (Jarden & Roache, 2023; Taylor, 2011). Various frameworks and indices, such as the OECD Framework for Measuring Well-Being and Progress, the Australian Unity Well-Being Index, Gross National Happiness, the Canadian Index of Wellbeing, and the Well-being of Nations, identify common key domains of well-being, which include health (H), wealth (W), environment (E), time use patterns (T), and social connections (S) (Cummins et al., 2003; Prescott-Allen, 2001; Smale & Hilbrecht, 2014; L. M. Smith et al., 2013; Ura et al., 2012). The relationship between key domains such as household economic status (Cummins, 2000; Diener et al., 1993; Ferrer-i-Carbonell, 2005), environmental factors including air pollution (Y. Li et al., 2019; Luechinger, 2009; Welsch, 2007; X. Zhang et al., 2017a), health status (Frijters et al., 2014; Ngamaba et al., 2017; Okun et al., 1984), and time use (Becchetti et al., 2012; Schmiedeberg & Schröder, 2017; Zuzanek, 1998) with well-being has been extensively studied.

Subjective measures of well-being, which encompass individuals’ self-assessed evaluations of their life, are commonly used metrics in empirical studies (Frey et al., 2010). Global life satisfaction, a key component of subjective well-being, frequently informs public policy assessments (Alesina et al., 2005; Layard et al., 2008). The Satisfaction with Life Scale closely aligns with the construct of well-being, offering a stable reflection of the general and enduring circumstances of people's lives (Diener, 2009; Helliwell & Barrington-Leigh, 2010). Such global evaluations account for the entirety of people's experiences, comprehensively quantifying quality of life.

Subjective well-being is particularly relevant when considering the impacts of energy transitions, which affect people's lives through multiple channels and across disparate dimensions of life. Theoretically, transitioning to clean energy has several positive impacts across key domains of well-being. Improved living environments (E) are characterized by better air quality and thermal comfort (Q. Li et al., 2017; J. Liu et al., 2016; J. Zhang et al., 2000). Enhanced health outcomes (H) result from decreased air pollution and reduced injury risks associated with the use of solid fuels (Kyayesimira & Florence, 2021; Lee et al., 2020; Perera, 2017; Zhu et al., 2023). Time savings (T) from more efficient cooking methods and reduced time spent collecting fuel can be reallocated to leisure, productive activities, or education, with significant benefits for women and children (Biswas & Das, 2022; Ding et al., 2014; Feng et al., 2009; Jagger et al., 2019). Moreover, transitioning to clean energy can boost social capital by enhancing social standing and encouraging pro-environmental behaviors (S) (Jeuland & Pattanayak, 2012; L. Li et al., 2022).

At the same time, the transition to clean energy could present significant challenges for households, particularly as many users of solid fuels reside in low-income areas where alternative, cleaner energy sources are often more costly. This economic disparity can exacerbate energy poverty, potentially leaving basic energy needs unmet or diverting funds from other essentials (Churchill et al., 2020; Igawa et al., 2022; Johnson et al., 2020; Nguyen et al., 2019; Riva et al., 2023; Xie et al., 2022). Additionally, clean energy technologies may clash with traditional habits, posing further challenges for adoption (Gould et al., 2022; Hollada et al., 2017; Lambe & Atteridge, 2012; Ochieng et al., 2020). These challenges can negatively impact people's well-being, as they struggle to integrate new energy sources into their daily lives.

The practical impact of energy transitions on well-being is thus complex and multifaceted, significantly influenced by interactions among various domains of well-being. For instance, while energy transitions can initially increase expenses and strain household budgets, they may also indirectly enhance wealth by boosting productivity through improved health and time savings, as well as by reducing medical costs (Duflo et al., 2008). This complexity is further compounded by variation in the level of household adherence to clean energy transitions. Field studies indicate that environmental and health benefits often fall short of expectations due to practices such as energy stacking (the mixing of solid and clean fuels) and the short-term abandonment of new technologies (Beltramo & Levine, 2013; Gould & Urpelainen, 2018; Hanna et al., 2016; Liao et al., 2021; Pope et al., 2017). Therefore, the complex mechanisms at play leave significant gaps in understanding the full effect of energy transitions on well-being.

Several studies have explored the impact of household energy transitions on subjective well-being, providing empirical evidence to fill existing knowledge gaps. Ma et al. (2022) used cross-sectional data from the 2016 China Labor-force Dynamics Survey to analyze how different cooking fuel types (clean-fuel-only, non-clean-fuel-only, and mixed-fuel) affected life satisfaction, measured on a five point scale.[1] They found that transitioning to complete clean-fuel use significantly increased life satisfaction. Specifically, the increase was 5.8 ($\pm$2.9) percentage points from non-clean-fuels and 3.4 ($\pm$2.0) percentage points from mixed-fuels. The impact of partial transitions (non-clean-fuel to mixed-fuels) was mild and statistically insignificant. In another study, Xie and Zhou (2021) used data from a cross-sectional field survey of approximately 4,000 rural households in Beijing to assess how the *Coal to Electricity* policy influenced subjective evaluations across five welfare dimensions (warmth, indoor air quality, cleanliness, convenience, and safety) using a 5-point Likert scale describing pos-

[1] They ask the life satisfaction as "Overall, how satisfied are you about your life? from 1–very unsatisfied, 2–unsatisfied, 3–fair; 4–happy; 5–very happy."

itive or negative changes in outcomes.[2] They reported that over 80% of households saw improvements in all dimensions post-policy. Instead of the "before and after" comparison, our pilot study (Barrington-Leigh et al., 2019) compared life satisfaction between treated and untreated villages in three Beijing districts with varying income levels. Using an 11-point scale, findings showed life satisfaction was 0.7 points higher in treated villages in the middle-income district but 1.0 points lower in treated villages in the low-income district, indicating variable impacts based on economic context.

This study aims to provide rigorous empirical evidence on how household energy transitions affect individuals' quality of life. The core research question addressed in this paper is: Do households living in villages implementing the *Clean Heating Policy* experience improvements in subjective well-being as a result of the energy transition? Under this core question, we address several related issues. First, on average, how does the *Clean Heating Policy* affect subjective well-being, including life satisfaction, satisfaction with living conditions, and satisfaction with income? Second, how does the impact on subjective well-being evolve over time? Third, which subgroups are more likely to experience improvements or deterioration in well-being due to the energy transition? Last, through which key domains does the *Clean Heating Policy* influence household subjective well-being? Leveraging the gradual implementation of the *Clean Heating Policy* in rural northern China, we adopt a quasi-experimental design to investigate these issues.

Our study makes significant contributions to the literature in four ways: (1) We prioritize the subjective evaluation of individuals involved in the energy transition, thereby enriching our understanding of its impact beyond the objective measures traditionally emphasized. (2) We focus on the less-studied area of energy transition in space heating, distinct from the more commonly discussed transitions in cooking energy, which involves different economic and environmental considerations, such as higher costs and impacts on thermal comfort. (3) This study contributes to the growing body of literature that employs subjective well-being measures to inform public policy decisions (Diener & Ryan, 2009). (4) Lastly, we conduct

[2] Point 3 refers to "similar to before"; greater than 3 indicates a better situation while less than 3 indicates a worse situation than before.

a rigorous impact evaluation using unique panel data from a large sample, which allows us to better control for unobservable confounders, a methodological improvement over most existing studies that rely on single-point comparisons of cross-sectional data.

The remainder of this paper is structured as follows: Section 4.2 provides the background and details of the *Clean Heating Policy* in Beijing. Section 4.3 outlines the study design, the data collected, and the empirical strategy used to evaluate the impacts. Section 4.4 presents the impacts of the *Clean Heating Policy* on subjective well-being and the robustness of our findings. Finally, Section 4.5 discusses the implications of the results and concludes the study.

4.2 *Clean Heating Policy* in Beijing

In this section, we introduce the background and the implementation of the *Clean Heating Policy* in Beijing.

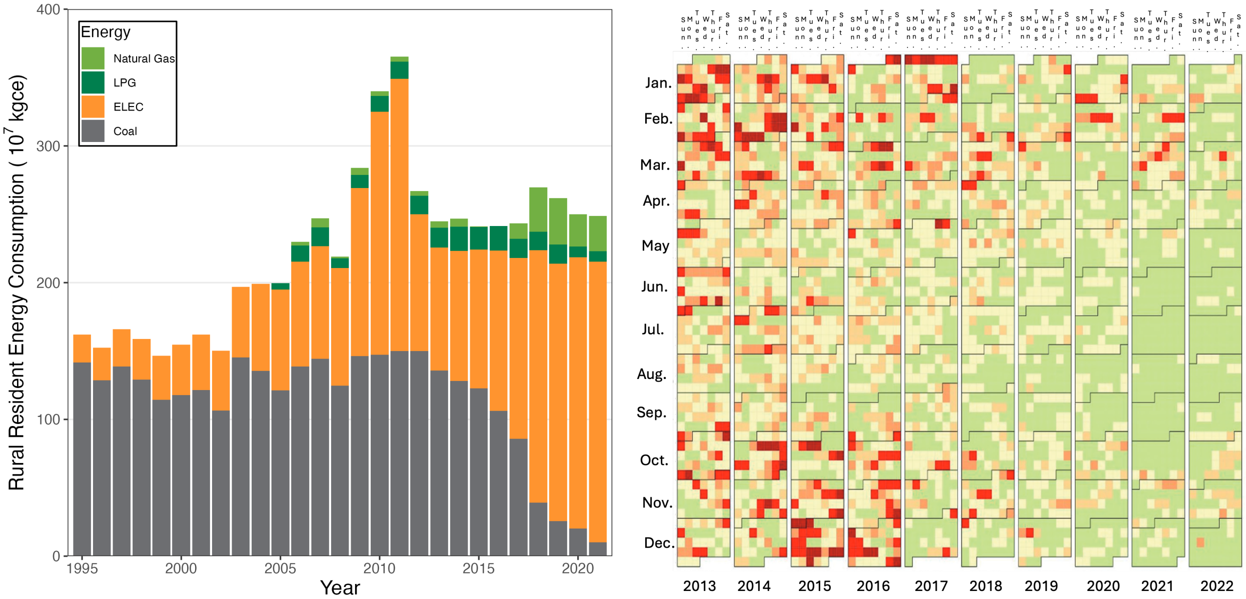
4.2.1 Background

Despite widespread rural electrification in Beijing since the 1980s, electricity was primarily used for lighting and appliances up until the end of the 1990s, due to supply instability and cost (Publicity Committee for Beijing's Rural Construction Achievements on the Thirty-fifth Anniversary of the Founding of the People's Republic of China, 1984). During this period, coal and biomass remained the primary energy sources for cooking and heating in rural households (Building Energy Research Centre at Tsinghua University, 2016). After-2000, gas fuels, especially LPG, rapidly gained popularity. As depicted in Figure 4.1a, LPG and natural gas consumption steadily increased from 2005, marking a significant shift in cooking energy sources. According to the Chinese Agricultural Census, the proportion of rural households in Beijing using gas as their primary cooking fuel rose dramatically from 9% in 1996 to 51% in 2006, and reached 90% by 2016. However, the transition to modern energy sources for space heating has been slower. Coal continued to be the dominant fuel, utilized in various stove types, including simple stoves, high-efficiency stoves, and private boilers (Tao et al., 2018). Figure 4.1a also shows a continuous increase in coal consumption by rural households between 1995 and 2013, with a typical household consuming between 2.5 to 3 tonnes of coal each heating season (Jingchao & Kotani, 2012; Yang et al., 2017).

In January 2013, Beijing recorded its worst pollution levels since the inception of $PM_{2.5}$ monitoring, with the monthly average concentration soaring to 160 μg/m^3, surpassing the WHO's annual average guideline by more than 30 times (Beijing Municipal Environmental Protection Bureau, 2014, p.3)(World Health Organization, 2021, p.78). This severe pollution event affected 8 million people and escalated into a significant social issue (Huang et al., 2014). In response, the Chinese Government and the Beijing Municipal Government launched the "Action Plan for Prevention and Control of Air Pollution" and the "Beijing Municipal Clean Air Action Plan 2013–2017," respectively, in 2013. These initiatives address air pollution by facilitating energy transitions across multiple sectors, including power production, transportation, industry, and residence. Figure 4.1b illustrates a pronounced correlation between the days of severe air pollution and the heating season, highlighting the urgent necessity for clean energy transitions away from coal-based space heating in rural households.

4.2.2 Implementation of the *Clean Heating Policy*

The *Clean Heating Policy*, initially piloted in 14 Beijing villages in 2013, aims to replace rural households' coal-based space heating with cleaner alternatives through the *Coal to Electricity* and *Coal to Natural Gas* schemes (Xinhua Net, 2017). Specifically, the *Coal to Electricity* policy has been widely adopted, with approximately 80% of Beijing's villages implementing this strategy by 2021 (Beijing Association for Sustainable Development, 2021). Consequently, this paper will primarily focus on this approach. As illustrated in Figure 4.2, the *Coal to Electricity* policy expanded rapidly between 2016 and 2018 following a successful three-year pilot phase and entered its final stage post-2019. The implementation began



(a) Rural household energy consumption in Beijing

(b) $PM_{2.5}$ pollution in Beijing between 2013 and 2022

Figure 4.1: Background of the *Clean Heating Policy* in Beijing. Data source for Figure 4.1a is China Energy Statistical Yearbook and Beijing Statistical Yearbook. All energy sources were converted to kilograms of standard coal (kgce), with 1 kgce equaling 29.3 MJ. A consistent conversion factor was used despite variations in energy quality over time. The 2012 decline in electricity consumption reflects urban/rural reclassification. Biomass fuels are excluded due to missing data. Figure 4.1b is obtained from 2022 Report on the State of the Ecology and Environment in Beijing (Beijing Municipal Ecology and Environment Bureau, 2023, p.4).

in the Six Urban Districts,[3] extended to the rural plain areas, and eventually reached the mountainous regions. The heating technology for the transition evolved from direct electric heaters to thermal storage heaters and ultimately to air source heat pumps (W. Liu, 2019). By the end of 2022, the policy had reached 1.35 million households across 3,557 villages, covering 90% of Beijing's villages and 93% of rural households with clean heating solutions (Cao, 2023).

[3]The six urban districts of Beijing encompass both the downtown core and the expanded surrounding urban areas: Dongcheng, Xicheng, Haidian, Chaoyang, Fengtai, and Shijingshan.

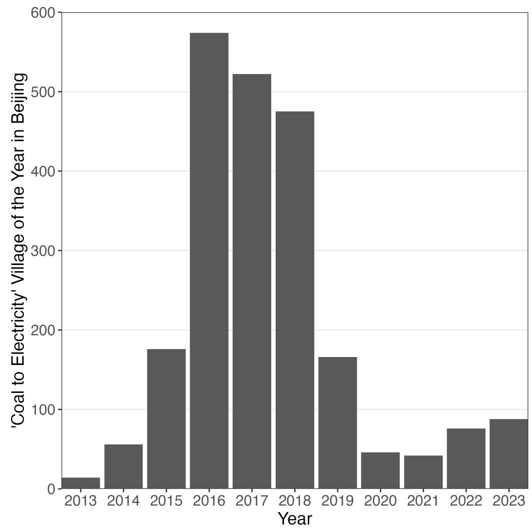


Figure 4.2: Number of villages implementing the *Coal to Electricity* policy per year during 2013–2023.

The *Coal to Electricity* policy consists of two key components: banning coal use and subsidizing electric heating systems. The ban on coal use was facilitated by the *Reduce and Substitute Coal Program*, which was introduced alongside the clean heating pilot. Since the 2013 pilot of the *Clean Heating Policy*, the *Reduce and Substitute Coal Program* has been gradually rolled out in villages not yet covered by the *Clean Heating Policy*. By 2017, all villages had transitioned to using high-quality and low-pollutant briquettes, collectively procured by district governments. Once a village adopts the *Clean Heating Policy*, it is prohibited from ordering coal from the district government, effectively cutting off household access to coal products.

Regarding subsidies, the government provides financial assistance for both the purchase of new electric heating systems and electricity consumption. Specifically, households receive 200 RMB/m^2 of heated area, up to a maximum of 24,000 RMB, for the purchase of air source heat pumps.[4,5] Additionally, households benefit from a discounted winter electricity tariff of

[4] As of March 2024, 1 RMB is approximately equal to 0.14 US dollars.

[5] Generous government subsidies significantly reduce the cost of air source heat pumps for rural households in Beijing, often making them essentially free for many families. For example, a household with a 120m^2 heating area can receive a six-horsepower air source heat pump at no cost. However, depending on the house size, the selected pump brand, and the desired capacity, some households may need to cover the excess beyond the maximum subsidy allowed.

0.1 RMB/kWh (compared to the standard rate of 0.48 RMB/kWh) for up to 10,000 kWh consumed between November 15th and March 15th annually (H. Liu & Mauzerall, 2020).

4.3 Study design and data

To assess the impact of the *Clean Heating Policy* on subjective well-being, we conducted three rounds of household surveys during the heating season across 50 villages in four districts of Beijing, spanning the period from 2018 to 2022. This section outlines the study's design, data collection methods, and the empirical strategy employed in the analysis

4.3.1 Study design and sample selection

Our household survey consisted of three rounds: a baseline survey followed by two rounds of follow-up surveys. The baseline survey, conducted between December 2018 and March 2019, collected data before the implementation of the Coal to Electricity policy in any of the sample villages. The first follow-up survey took place between November 2019 and January 2020, after the policy had been initiated in ten villages. By the second follow-up survey, conducted in the winter of 2021, another ten villages had joined the policy, with seven sample villages receiving the treatment in 2020 and three in 2021. Figure 4.3 illustrates the geographic distribution and the timing of policy adoption in the sampled villages.

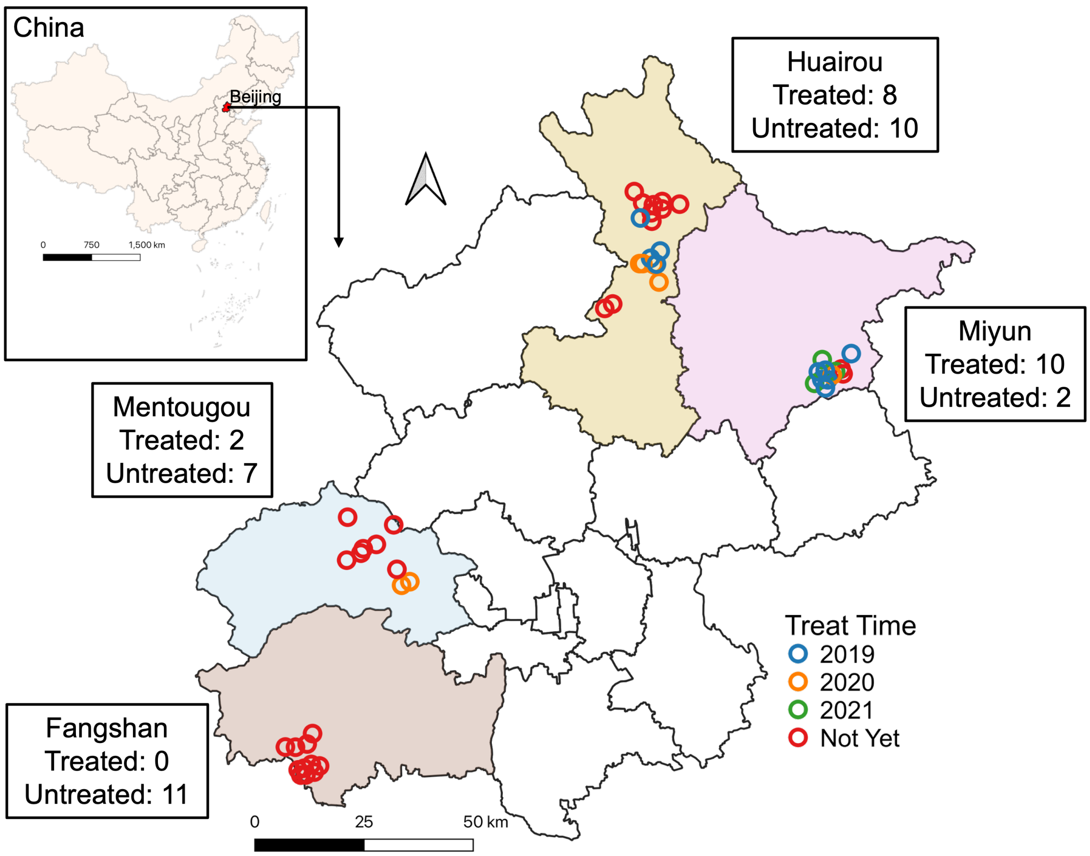


Figure 4.3: Sampling strategy and treatment status of sample villages.

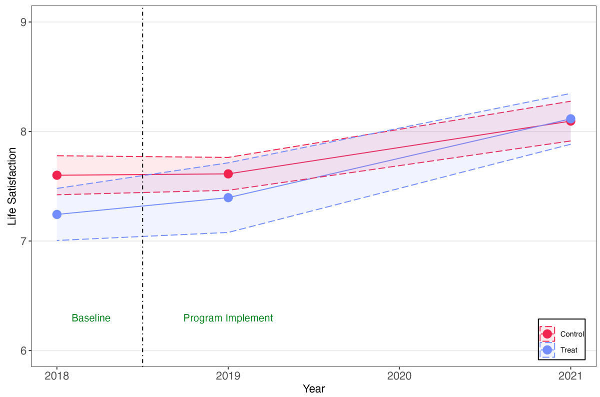
Our baseline survey, conducted in the winter of 2018, occurred three years after the widespread implementation of the *Clean Heating Policy* in rural Beijing. Consequently, finding villages that had not yet adopted the policy for random sampling presented challenges. The study focused on four remote suburban districts — Fangshan, Huairou, Mentougou, and Miyun — situated on the northeastern and southwestern borders of Beijing. Within each district, we selected a varying number of villages from one or two towns, ranging from nine villages in Mentougou to eighteen in Huairou. Due to the low winter occupancy rates in rural Beijing, we collaborated with village leaders to semi-randomly select approximately 20 households likely to be present during the baseline survey. For subsequent follow-up surveys, we prioritized revisiting baseline participants. If they were unavailable or declined to participate, we recruited new participants to maintain the required sample size per village.

4.3.2 Data

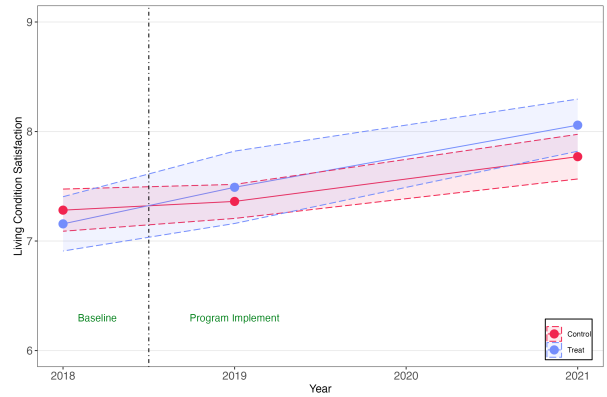
This study collected first-hand survey data through face-to-face interviews conducted by approximately 15 trained enumerators each season. They used survey software on handheld tablets — Surveybe for the baseline and first follow-up, and ODK Collect for the second follow-up. Each household interview lasted approximately 45 minutes.

The primary outcome, subjective well-being, was measured using the standard life satisfaction question: "Taking all things into account, how satisfied are you with life as a whole these days?" Respondents rated their satisfaction on an 11-point scale, ranging from 0 (completely unsatisfied) to 10 (completely satisfied). Various life satisfaction scales — such as 3-point, 5-point, 7-point, 10-point, and 11-point — have been employed in surveys (Barrington-Leigh & Lemermeyer, 2023; Helliwell et al., 2019). Research indicates that odd-numbered scales with more response categories tend to offer greater reliability (Kroh, 2006), leading us to adopt the 0–10 scale. Besides overall life satisfaction, we included two other subjective assessments: satisfaction with living conditions ("How satisfied are you with your living conditions as a whole?") and satisfaction with income ("How satisfied are you with the income of your household?"), both also measured on the same 11-point scale. These measures enable us to explore impacts on two critical well-being domains: environment and wealth.

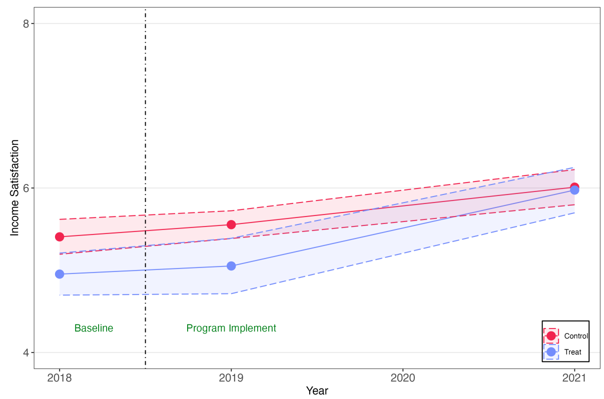
Figure 4.4 illustrates the trends in overall life satisfaction, satisfaction with living conditions, and satisfaction with income for both the control and treatment groups over time. At baseline, households in the control group reported slightly higher scores across all three measures compared to those later covered by the *Clean Heating Policy*. At baseline, life satisfaction and satisfaction with living conditions in the treatment group both averaged 7.2, while satisfaction with income averaged 5.0 (on a 0–10 scale). Following the policy's implementation, the treatment group experienced significant increases in all three subjective well-being outcomes. By 2021, the final year of the study, life satisfaction, satisfaction with living conditions, and satisfaction with income in the treatment group had increased by 0.9, 0.9, and 1.0 points respectively, compared to their baseline levels.



(a) Life satisfaction



(b) Satisfaction with living conditions



(c) Satisfaction with income

Figure 4.4: Time trends of outcome variables of treat and control groups. This figure shows the time trends of (a) life satisfaction, (b) satisfaction with living conditions, and (c) satisfaction with income of different groups over time. Red and blue denote the control and treatment groups, respectively. The vertical dashed line separates pre- and post-implementation of the *Clean Heating Policy*. To the left of the line, "Treat" statistics reflect baseline conditions for households that later received the treatment. To the right of the line, "Treat" and "Control" statistics represent post-treatment and not-yet-treated conditions for that year. Dots show mean satisfaction, and shaded areas indicate 95% confidence intervals.

Strictly speaking, these variables measure the subjective well-being of the individual within the household who responded to the survey questions. Due to the study design, the names of the participants who answered the subjective well-being questions were not recorded. Therefore, we cannot guarantee that the responses were provided by the same individuals across all survey years. To account for important time-invariant factors that significantly influence subjective well-being, we treat the data as a household-level panel. This approach is based on two key considerations: First, life satisfaction tends to be highly correlated among family members, particularly spouses (Schimmack & Lucas, 2007). Over 60% of our sample households consisted of a middle-aged or elderly couple, suggesting that an individual's response can reasonably represent the "household" level of life satisfaction. Second, unlike the pronounced gender differences observed in the literature on cooking energy transitions, gender plays a relatively minor role in coal-based heating practices in rural northern China. Given the absence of a clear gender division of labor in heating-related activities within the sample area, it is reasonable to assume that the policy's impact on subjective well-being is similar for individuals within the same household.

Given that the *Clean Heating Policy* is implemented at the village level, the independent variable — household treatment status of the *Clean Heating Policy* — is determined by whether their village has completed the policy.[6] Each summer, the Beijing municipal government publishes a list of villages scheduled for inclusion in the policy. Subsequently, the power company upgrades the necessary equipment and grid infrastructure in those villages. In the fall, the village committee selects the brand of air source heat pump to be installed, and the company completes installations in all village homes before the heating season begins.

We also collected information on a variety of factors including household sociodemographic characteristics (e.g., family size, education, marital status, income, and assets), housing characteristics (e.g., house area, age, and insulation), fuel consumption patterns (e.g., type, usage, quantity, and price), heating practices (e.g., method and duration), health status (for health survey participants, including measures like blood pressure and respiratory symptoms), and living environment conditions (e.g., indoor and outdoor temperature and air quality). We selected data from these categories to conduct a preliminary exploration of

[6] Fewer than 5% of households in treated villages opted to postpone their heating pump installation to the following year due to ongoing house renovations. We consider this postponement part of policy compliance and include it in the treatment effects.

the potential mechanisms through which the *Clean Heating Policy* may have influenced key domains of subjective well-being.

Table 4.1 presents descriptive statistics for selected village and household sociodemographic characteristics, grouped by the timing of the *Clean Heating Policy* implementation. Panel A illustrates that, compared to treated villages — which average 200 households, 500 people, and a per capita income of approximately 18,000 RMB in 2015 — never-treated villages tend to have more households and a larger population, but a lower per capita income. This discrepancy is likely due to the fact that 11 of the 30 never-treated villages are located in a town in Fangshan district, where the substation was overloaded and thus lacked the capacity to participate in the *Clean Heating Policy* during our study period.

The difference between sample villages in Fangshan and the other three districts is also evident in air pollution levels. Positioned on the Beijing-Hebei border, villages in Fangshan experienced higher heating-season $PM_{2.5}$ and black carbon concentrations at baseline, likely due to pollution transmission from Hebei province (H. Zhang et al., 2016). Additionally, while briquette prices remained stable in the other districts throughout our study, villages in Fangshan saw a doubling of prices in the final study year. We address the potential implications of these Fangshan-specific discrepancies for the robustness of our results in Section 4.4.4.

Panel B in Table 4.1 presents the sociodemographic and housing characteristics of sample households, categorized by the timing of treatment. On average, treated households comprise 2.3 family members, with 1.2 labor-force participants aged 16–65, primarily engaged in local agricultural work. Most households have limited formal education, with only 20% having completed secondary school or higher. The average weekly meat expenditure per family is 39 RMB, while monthly mobile phone bills average 85 RMB. The average house size is 127 m^2, and the average house age is 19 years. Additionally, we considered factors known to influence life satisfaction, particularly the age and marital status of the primary respondent to the household health survey (Palmore & Luikart, 1972). 86% of respondents were married and in their early 60s. As shown in the final column, untreated households exhibit characteristics comparable to those of treated households across all measured variables.

Table 4.1: Descriptive statistics. Village-level data in Panel A, including household counts, population figures, and per capita income, were sourced from the 2016 Statistical Yearbook of the four sampled districts, reflecting conditions prior to policy implementation in 2015. Methods for measuring the average baseline $PM_{2.5}$ and BC concentrations are detailed in the supplementary materials (Text S4) of our previous study X. Li et al. (2022). We treated the data as pooled data to present the descriptive statistics.

	Explain	*Clean Heating Policy* Treatment time			
		2019	2020	2021	Never Treat
Panel A. Village characteristics					
Households	Number of households	250	219	197	375
Population	Number of population	572	486	404	662
Capita Income	Per capita income (RMB)	19500	18100	17300	12900
Distance	Straight-line distance from the village committee to the city center (kilometers)	84.4	65.5	82.5	71.7
Altitude	Altitude of the Village (meters)	274	264	338	281
$PM_{2.5}$	Average $PM_{2.5}$ concentration in baseline heating season ($\mu g/m^3$)	29.6	20.7	31.7	42.7
Black carbon	Average black carbon concentration in baseline heating season ($\mu g/m^3$)	1.36	1.07	1.13	1.56
Panel B. Selected Household Characteristics					
Family size	Population resident in winter	2.31	2.21	2.30	2.41
Labor	Labor force population aged 16–65	1.27	1.17	1.25	1.38
Middle school	Household's highest level of education is middle school and above (1–Yes; 0–No)	0.241	0.260	0.163	0.302
Meat	Average meat expenditure (raw or cooked) per week (RMB/week)	37.7	41.6	36.3	32.6
Mobile	Mobile phone expenditure last month (RMB/month)	89.5	84.7	70.6	91.9
House area	House area (m^2)	127	127	127	127
House age	Age of the house (years)	19.0	17.3	21.7	19.6
Married	Marital status of health survey participant (1–married; 0–divorced, widowed, or never married)	0.842	0.843	0.958	0.883
Age	Age of health survey participant	61.4	63.4	60.9	61.4
Number of villages		10	7	3	30
Number of households		244	173	70	719
Number of observations		609	415	166	1760

4.3.3 Identification strategy

Leveraging the quasi-experiment created by the staggered implementation of the *Clean Heating Policy*, we employed a difference-in-differences (DiD) strategy to estimate the impacts of this household energy transition intervention on subjective well-being. This strategy compares changes in outcomes before and after policy implementation between households in treatment villages (where the policy was implemented) and control villages (where the policy had not yet been implemented). Our baseline specification employs a two-way fixed effects (TWFE) model, which is specified as follows:

$$Y_{it} = \mu_i + \lambda_t + \beta \times \text{Treat}_{it} + X_{it} \times \gamma + \epsilon_{it} \tag{4.1}$$

where Y_{it} represents the measures of subjective well-beings (i.e., life satisfaction, satisfaction with living conditions, and satisfaction with income) of household i who participated in survey of year t; Treat_{it} is a binary indicator variable that equals 1 if household i participated in the *Clean Heating Policy* (in the village completed the policy) in survey year t, and 0 otherwise. X_{it} is a vector of time-variant household-level controls. μ_i indicates the household-level fixed effects that control for household's time-invariant characteristics to account for various time-invariant factors (e.g., personal traits) that can affect subjective well-being; λ_t indicates the survey-year t fixed effects that address concerns regarding the influence of common trends in life satisfaction across households over time. For instance, strict enforcement of mandatory home quarantine during the Covid-19 pandemic in China could impact all people's life.

Identifying confounding factors, X_{it}, in the context of the *Clean Heating Policy* is challenging. In the early stages of the policy, several factors were important for village eligibility as mentioned in government documents. These include village altitude, grid supply capacity, and completion of energy efficiency and insulation retrofits in houses.[7] Additionally,

[7]Since 2006, Beijing has implemented an earthquake-resistant and energy-saving retrofitting project for rural dwellings, offering subsidies or incentives to families who undertake earthquake-resistant reinforcement and energy-saving and heat preservation retrofits during house renovations. According to some policy doc-

eligibility criteria stipulated that a village should not be a proposed site for demolition and renovation in the upcoming five-year regional plan (Beijing Municipal People's Government, 2016). To our knowledge, the government did not explicitly publish criteria for prioritizing villages for policy inclusion after the initial phases, especially in mountainous areas. Unfortunately, we lack quantitative data on factors such as completion of retrofitting projects or inclusion in demolition plans for the sample villages. While these criteria might be partially captured by fixed effects, such as village altitude and grid capacity, we also control for building age (reflecting the likelihood of isolation and demolition) and house area (which influences the capacity of subsidized heating pumps) in our preferred specification.

The key assumption of our DiD approach is the parallel trends assumption, which assumes that in the absence of the *Clean Heating Policy*, the life satisfaction — as well as satisfaction with living conditions and income — of households in both treatment and control groups would have followed the same trajectory over time. Under this assumption, and assuming that the average treatment effects are consistent across treated households and over time, the coefficient of interest, β, on Treat_{it} identifies the average treatment effect of the *Clean Heating Policy* on household subjective well-being.

We estimate Equation 4.1 using ordinary least squares (OLS). In regression analyses where subjective well-being indicators, such as life satisfaction, serve as the dependent variable, there is ongoing debate about whether these measures should be treated as ordinal or cardinal (Schröder & Yitzhaki, 2017). Ordinal comparability assumes only a valid and unique ranking, whereas cardinal comparability additionally assumes equal intervals between scale points. Given concerns such as larger gaps at scale extremes (Ng, 2008) — empirical economics studies often favor the more conservative ordinal assumption. Under this approach, ordered latent-response models (e.g., ordered logit or probit) are typically employed when the response categories are discrete (e.g., very unsatisfied, unsatisfied, fair, satisfied, very satisfied) (Angelini et al., 2012; Litchfield et al., 2012; Zhou & Yu, 2017).

uments, the completion of these programs may be an early criterion for identifying villages for inclusion in the *Clean Heating Policy* (Beijing Association for Sustainable Development, 2021).

However, recent research has increasingly adopted the cardinal comparability assumption for numeric measures of subjective well-being, primarily for statistical convenience. This approach allows for the straightforward inclusion of fixed-effect terms to control for unobserved factors and facilitates intuitive interpretation of results (Kristoffersen, 2017). Plant (2024) investigates whether life satisfaction scales can be considered cardinal by examining the extent of their deviation from cardinality. Their findings suggest that any such deviations are minimal, if present at all, thereby justifying the treatment of subjective well-being scales as cardinal in empirical analysis. Moreover, Ferrer-i-Carbonell and Frijters (2004) demonstrated that the choice between cardinal and ordinal treatment has relatively little impact on results, while the inclusion of time-invariant fixed effects for personality traits is crucial. Consequently, we use OLS to estimate our TWFE regression model, with standard errors clustered at the village level.

Although the parallel trends assumption is fundamental to the DiD approach, it is inherently untestable, as we cannot observe counterfactual outcomes for the treatment group. To assess its plausibility in our context, we go beyond the baseline regression and conduct an event study (Equation 4.2) to examine pre-treatment trends. The post-treatment results from this event study also provide insights into the dynamic effects of the *Clean Heating Policy* on subjective well-being.

$$Y_{it} = \sum_{j=1}^{3} \theta_{-j} \times \text{Treat}_{ij} + \sum_{k=0}^{2} \beta_k \times \text{Treat}_{ik} + X_{it} \times \gamma + \mu_i + \lambda_t + \epsilon_{it} \tag{4.2}$$

The *Clean Heating Policy* is implemented in year 0, while j leads and k lags are included. θ_j and β_k correspond to pre-trends and dynamic effects j or k periods from the policy implementation (Clarke & Tapia-Schythe, 2021; Cunningham, 2021).[8]

While TWFE regressions, as specified in Equation 4.1, are commonly used for DiD models, recent literature points out that they may produce biased estimates of treatment effects in staggered adoption designs (De Chaisemartin & d'Haultfoeuille, 2023). Goodman-Bacon

[8]Our baseline TWFE event study regression omits the first Pre (one period prior to the policy) to reflect the baseline difference, where $j = 1$. This could vary for other heterogeneity-robust estimators, which is detailed in the figure notes.

(2021) demonstrates that the TWFE estimator represents a weighted average of all possible 2×2 DiD comparisons between groups treated at different times in staggered DiD settings. This estimator consistently captures the average treatment effect on the treated (ATT) only if the treatment effects are uniform across treated groups and over time. However, the assumption of homogeneous treatment effects is rarely met in practice, which raises concerns about the validity of classic TWFE estimation in staggered DiD designs.

Given the gradual implementation of the *Clean Heating Policy*, we replicated our analysis using various heterogeneity-robust DiD estimators introduced by Sun and Abraham (2021), Gardner (2022), Callaway and Sant'Anna (2021), De Chaisemartin and d'Haultfoeuille (2020), Borusyak et al. (2021), and Wooldridge (2021) to address potential biases in our baseline TWFE estimation. Additionally, we applied the Bacon Decomposition method to assess heterogeneity across different 2×2 DiD comparisons (Goodman-Bacon, 2021). This decomposition allows us to diagnose any variation in treatment effects and quantify how the staggered implementation of the *Clean Heating Policy* may have influenced the TWFE estimates of average treatment effects. The results of the bacon decomposition are presented in Appendix C.1

It is conceivable that the policy's impact varying according to household's preexisting characteristics, such as the differences in economic and space heating outcomes for households with or without pre-existing radiator systems noted in the previous chapter. Additionally, individual perceptions of the policy's effects may differ. For example, those with pre-existing respiratory conditions might report a more pronounced improvement in quality of life, attributable to the policy's beneficial effects on indoor air quality. To investigate these heterogeneous treatment effects, we estimate a modified version of Equation 4.1 by incorporating an interaction term between treatment status Treat_{it} and baseline characteristic groups C_i (e.g., wealth index, age, and self-reported health status of the health survey participant) for household i, as shown in Equation 4.3.

$$Y_{it} = \beta \times \text{Treat}_{it} \times C_i + X_{it} \times \gamma + \mu_i + \lambda_t + \epsilon_{it} \tag{4.3}$$

Assuming that certain subpopulations, based on their baseline characteristics, are more likely to be affected by the *Clean Heating Policy* and exhibit greater impacts in specific domains, this heterogeneity analysis provides insights into the mechanisms underlying the policy's well-being effects (Braghieri et al., 2022). For example, if improved health is a key mechanism through which the policy affects subjective well-being, we would expect to see a larger impact on households reporting poor health at baseline.

We also preliminarily explore mechanisms through Bootstrapped Mediation analysis, a technique more commonly used in epidemiology and psychology, which relies on information from three mediation equations (i.e., the baseline regression in Equation 4.1, and Equations 4.4 and 4.5, Judd & Kenny, 1981; MacKinnon et al., 2007).[9] Mediation analysis allows us to understand how households subjectively experience the impact of energy transitions on their life through key dimensions of well-being. Therefore, further aiding our understanding of the pathways through which energy transition contributes to improvements in subjective well-being.

$$Y_{it} = \beta' \times \text{Treat}_{it} + X_{it} \times \gamma' + \theta M_{it} + \mu_i + \lambda_t + \epsilon'_{it} \tag{4.4}$$

$$M_{it} = X_{it} \times \gamma'' + \theta' \text{Treat}_{it} + \mu_i + \lambda_t + \epsilon''_{it} \tag{4.5}$$

The "indirect effect," calculated either as $\beta - \beta'$ or $\theta\theta'$, represents the treatment effect mediated by the variable M. We use bootstrap estimation to determine the statistical significance of the mediation effects and to provide confidence intervals for the "indirect effects," $\theta\theta'$, through repeated randomized sub-sampling with replacement (Hayes, 2017; Mallinckrodt et al., 2006; Shrout & Bolger, 2002).

Due to the complex generation process of observational data, concerns regarding the endogeneity of mediators make the use of mediation analysis to explore mechanisms less common in economic studies. For instance, if we include a health indicator as a mediator of the policy's impacts on subjective well-being in our baseline estimate, omitting factors like indoor air quality (which influences both health and subjective well-being) could lead

[9] We consider here only scenarios with a single mediator.

to inconsistent coefficient estimates in Equation 4.4. From a causal inference perspective, adding the mediator M in Equation 4.4 is analogous to introducing a confounding variable in Equation 4.2, resulting in biased estimates of β' (Jiang, 2022). Therefore, our mechanism analysis using mediation should be interpreted as an exploratory investigation of correlations rather than a definitive establishment of causal pathways.

4.4 Results

In this section, we first examine the average treatment effects of the *Clean Heating Policy* on three subjective well-being indicators: life satisfaction, satisfaction with living conditions, and satisfaction with income. We then discuss the dynamic treatment effects observed through the event study. Finally, we explore heterogeneous treatment effects among subgroups of sample households to identify those likely to experience greater benefits or detriments to their well-being from the household space heating intervention.

4.4.1 Main results

Table 4.2 presents the TWFE estimates of β from Equation 4.1, illustrating the average impact of the *Clean Heating Policy* on household life satisfaction (columns 1–3), satisfaction with living conditions (columns 4–6), and satisfaction with income (columns 7–9). The first column for each dependent variable (columns 1, 4, and 7) shows the results of the TWFE estimator with village and year fixed effects, without control variables. The second column for each dependent variable (columns 2, 5, and 8) includes household and year fixed effects, but no control variables. The final column for each dependent variable (columns 3, 6, and 9) includes both household and year fixed effects, as well as control variables. To further address potential endogeneity arising from unobserved time-varying household characteristics, we also introduce interactive fixed effects for household and year, allowing the impact of unobserved household factors to evolve over time. This serves as a robustness check for our main results (Bai, 2009), with findings detailed in Table C.1 in Appendix C.2.

We first discuss the average effect of the *Clean Heating Policy* on life satisfaction. Across various model specifications (columns 1–3), the results are consistent. Our preferred specification (column 3) shows that policy implementation increased life satisfaction by 0.36 points on a 0–10 scale, representing a 5% increase compared to the average life satisfaction of 7.67 in households not yet enrolled. This average impact aligns with the range observed in our previous cross-sectional pilot study, where treated villages in low-income districts experienced a 1.0-point decrease, while those in middle-income districts saw a 0.7-point increase (Barrington-Leigh et al., 2019). This result is also comparable to findings from other studies on the impact of rural household energy transitions in China (Ma et al., 2022). N. Li (2023), leveraging the "Solar Energy for Poverty Alleviation Program (SEPAP)" as a quasi-experiment, found that clean energy use increased life satisfaction by 0.35 ($\pm$0.22) points on a 0–10 scale.[10] The substantial increase in R^2 between columns (1) and (2) highlights that a most portion of the variation in life satisfaction is explained by time-invariant fixed effects.

To provide context for the magnitude of our main estimations, we offer several benchmarks. First, a simple regression of life satisfaction on family income shows that a 1-unit increase in the logarithm of family income (equivalent to an increase by a factor of e, or 2.718) predicts a 0.44-point increase in life satisfaction. Thus, our estimated *Clean Heating Policy* impact of 0.36 points is comparable to a 126% increase in family income. When replicating this model using TWFE regression with household and year fixed effects, the income effect reduces to 0.16, making the policy's impact equivalent to an even larger income increase. Given the policy's primary objective of improving air quality, we benchmark our estimates against relevant studies. Specifically, the policy's impact on life satisfaction is approximately equivalent to a decrease of 290 μg/m^3 in outdoor $PM_{2.5}$ concentrations (X. Zhang et al., 2017b),[11] and similarly, to a 22.5 μg/m^3 reduction in outdoor SO_2 concen-

[10] Converted from 1–5 to 0–10 life satisfaction scale. The SEPAP deploys distributed solar photovoltaic (PV) systems to more than 2 million households in 35,000 villages in impoverished areas from 2014 to 2020. On top of meeting the household's own electricity needs, additional power generation will be connected to the grid thereby increasing income for rural households (Geall et al., 2018). The original results are in column (6) of Table 7.2 on page 127.

[11] Converted from a 0–4 to a 0–10 life satisfaction scale. The original results are presented in column (1) of Table 2.

trations(Ferreira et al., 2013).[12] Considering the predominance of elderly residents in rural areas, we also compare our estimates to determinants of elderly life satisfaction in China. Relative to W. Zhang and Liu (2007), the policy's impact is about 12% of the effect of receiving adequate medical services and 58% of the effect of having a pension.[13]

Unlike global life satisfaction, satisfaction with key well-being domains has received less attention in empirical studies. As shown in Column (6), the *Clean Heating Policy* increased household satisfaction with living conditions by 0.26 points on a 0–10 scale. We did not define "living conditions" in the survey question to allow respondents to consider any relevant factors, such as indoor and outdoor cleanliness, air quality, noise, thermal comfort, and safety. Our previous chapter demonstrated that the *Clean Heating Policy* significantly increased indoor temperatures, while our forthcoming analysis reports a reduction in air pollution — both of which support the positive impact on satisfaction with living conditions. Additionally, survey respondents frequently cited improved house cleanliness, reduced risk of carbon monoxide poisoning, and the convenience of no longer handling coal as key benefits of the policy. Similarly, Xie and Zhou (2021) found that over 80% of rural Beijing households reported improvements in warmth, indoor air quality, cleanliness, convenience, and safety following the implementation of the *Clean Heating Policy*. However, the policy also has some drawbacks regarding living conditions. For instance, approximately 25% of treated households in the final wave of the survey reported being somewhat annoyed by the noise from air-source heat pump operation.

Given that using clean energy for space heating generally costs more than solid fuels, households with constant income may allocate less to other goods and services, potentially reducing satisfaction with income. As shown in Column (9) of Table 4.2, the *Clean Heating Policy* increased satisfaction with income by 0.1 points on a 0–10 scale, equating to a 2% increase for households not covered by the policy — though this effect is small and statistically insignificant. This finding seems to contradict our previous observation of a slight increase

[12]The original findings are documented in column (2) of Table 3.

[13]Converted from a 1–4 to a 0–10 life satisfaction scale. The original results are in column "Model II" of Table 4.

in winter energy expenditure as a proportion of household income. Potential explanations include satisfaction with the goods and services that income affords, rising absolute income, increased marginal benefit due to the extra heat pump capital, and complex relationships between expenditure and satisfaction with income.

In the previous chapter, we excluded observations from Fangshan during the final season to avoid the confounding effects of an unexpected briquette price increase, which could threaten the parallel trends assumption for economic outcomes. When we replicate the regression of satisfaction with income using the same sample as the previous chapter, the estimated impact of the *Clean Heating Policy* on satisfaction with income further decreases to 0.05 ($\pm$0.41). Additionally, using per capita income as the dependent variable in a TWFE regression shows that the policy results in a non-significant increase of 602 RMB (with a standard error of 1,707 RMB). Decomposing income sources reveals small, non-significant increases in wage and government subsidy income, the latter reflecting additional government subsidies for impoverished households to offset increased energy costs. Moreover, given that heating is a basic necessity, a slight increase in heating costs, accompanied by a significant improvement in heating quality, might not necessarily lead to reduced satisfaction with income.

When we further include the interaction term for household and year fixed effects in the regression (as shown in Table C.1 in Appendix C.2), the point estimate of the policy's average impact on satisfaction with income becomes negative (-0.17 ± 0.8) but remains small and statistically insignificant. Overall, despite raising household energy costs, the *Clean Heating Policy* has no significant adverse effect on satisfaction with income.

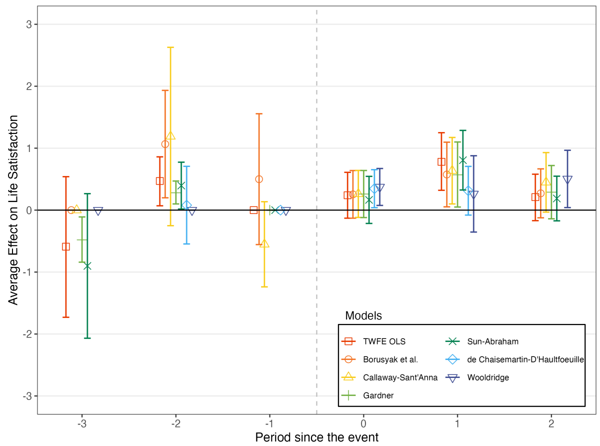
Furthermore, we estimated the average treatment effects using various heterogeneity-robust DiD estimators as a robustness check. The results, presented in Figure C.2 in the appendix, demonstrate consistency with the baseline regression results obtained with TWFE estimator.

Table 4.2: Baseline regression results: average treatment effects of the *Clean Heating Policy*. Each column of estimate is from a separate regression based on the identical dataset but with different combinations of fixed effect terms and controls. Due to singleton observations (households appearing in only one survey round), 160 observations were dropped when including household fixed effects in the analysis. Standard errors in parentheses are clustered at the village level. * p < 0.1, ** p < 0.05, *** p <0.01.

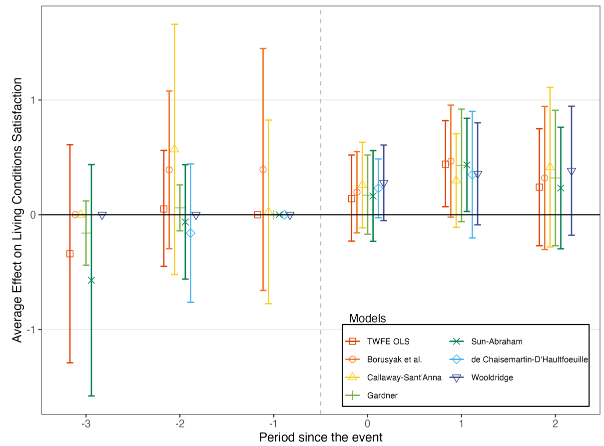
	Life Satisfaction			Satisfaction with Living Conditions			Satisfaction with Income		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment	0.38***	0.35**	0.36**	0.34**	0.26*	0.26*	0.19	0.11	0.10
	(0.12)	(0.14)	(0.14)	(0.14)	(0.15)	(0.14)	(0.20)	(0.20)	(0.20)
Num.Obs.	2,949	2,789	2,789	2,949	2,789	2,789	2,949	2,789	2,789
R^2	0.06	0.56	0.56	0.06	0.53	0.54	0.09	0.58	0.58
Mean Dep.Var.	7.71	7.70	7.70	7.50	7.50	7.50	5.56	5.55	5.55
Village FE	✓			✓			✓		
Household FE		✓	✓		✓	✓		✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls			✓			✓			✓

Figure 4.5 presents event study plots to assess the parallel trends assumption and examine the dynamics of treatment effects over time. In this analysis, indicators for leads and lags, in years, the implementation of the *Clean Heating Policy* were included. To account for potential heterogeneity in treatment effects across time and units, event study figures were generated using a set of recently developed heterogeneity-robust estimators, alongside the traditional TWFE estimator. However, caution is warranted when comparing results from different estimation methods, particularly regarding pre-treatment effects, as these methods handle staggered settings and construct control groups differently (Roth, 2024; Wing et al., 2024).

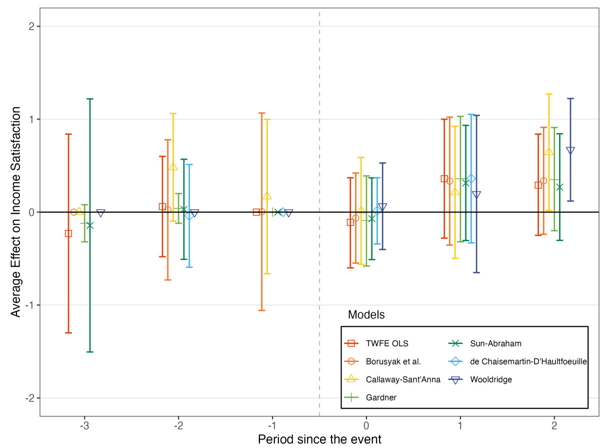
The right side of the vertical dotted line in Figure 4.5 depicts the post-treatment effects of the *Clean Heating Policy* on subjective well-being. Both the traditional TWFE and heterogeneity-robust estimators yield similar results, indicating relatively consistent impacts over time. However, event study figures (Figures 4.5a, 4.5b, and 4.5c) reveal subtle variations in impacts across years. Life satisfaction and satisfaction with living conditions follow an inverted U-shaped pattern, while satisfaction with income exhibits an inverted J-shape. Considering our fieldwork typically began in early winter, households in the policy's first year (period 0 in Figure 4.5) had limited exposure to its full effects. As a result, initial impacts may reflect concerns such as financial anxiety over increased electricity bills, which could explain the negative point estimate for period 0 in Figure 4.5c. The positive point estimates for subjective well-being in subsequent years likely reflect households' full experience of the lifestyle changes brought about by the policy.



(a) Life satisfaction



(b) Satisfaction with living conditions



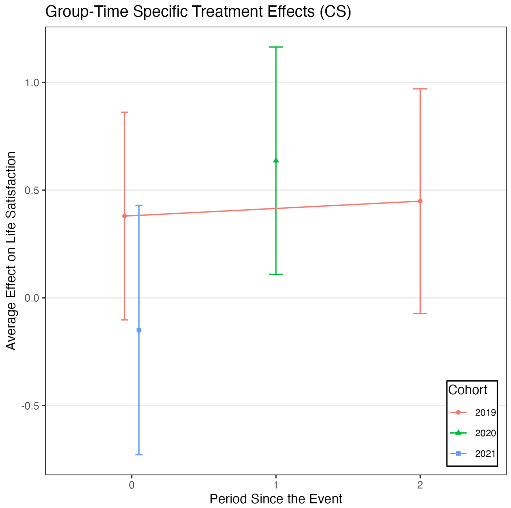
(c) Satisfaction with income

Figure 4.5: Dynamic treatment effects of the *Clean Heating Policy* on subjective well-being. This figure shows the event-study plots constructed using seven different estimator on (a) life satisfaction, (b) satisfaction with living conditions, and (c) satisfaction with income. Each color of the points and error bars signifies results obtained from DiD estimators. See the note of Figure 3.4 for some details. Borusyak et al. (2021) and Callaway and Sant'Anna (2021) not taking fixed reference period like other estimators of pre-treamtent estimation. This issue of reference period for pre-treatment estimations in event studies has been discussed in detail Roth (2024). Standard errors are clustered at the village level.

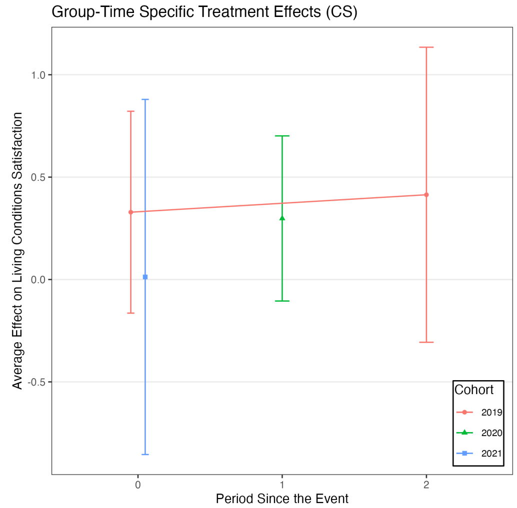
The slight decline in life satisfaction and satisfaction with living conditions in the second year may be attributed to adaptation, a key mechanism explaining changes in subjective well-being over time (Luhmann et al., 2012). However, given the study's short duration and missing data due to the year gap, the observed changes in the event study could also reflect cohort effects. We explore this possibility using group-time-specific estimations from Callaway and Sant'Anna (2021) and Wooldridge (2021). As shown in the first row of Figure 4.6, the Callaway and Sant'Anna (2021) estimator suggests cohort effects across all three well-being indicators. Households that received the *Clean Heating Policy* in 2021, during the COVID-19 outbreak, experienced lower initial impacts compared to those treated in 2019.

The Wooldridge (2021) estimator similarly shows cohort effects for satisfaction with living conditions and satisfaction with income (Figures 4.6e and 4.6f), though the effect on life satisfaction is less pronounced. Furthermore, a comparison of the impacts in year 0 and year 2 for the 2019 cohort (Figures 4.6c and 4.6f) reveals that satisfaction with income significantly increased two years after treatment, exceeding the initial "prediction" effect observed in year 0. Due to data limitations, we cannot provide extensive insights into the policy's long-term impact, which warrants further investigation in future studies.

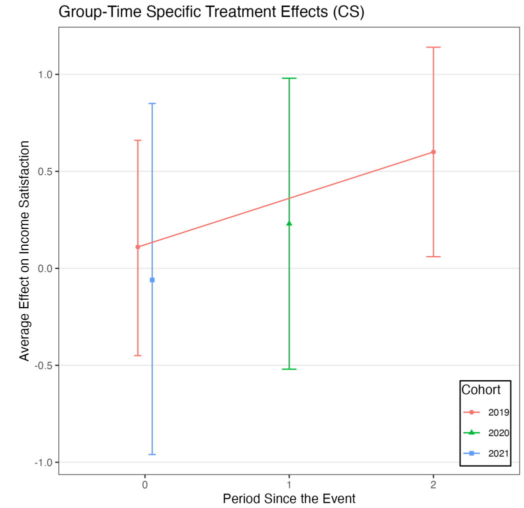
The pre-treatment estimations of satisfaction with living conditions and satisfaction with income impacts, as shown in the left panels of Figures 4.5b and 4.5c, support the parallel trends assumption. Results from all estimators are statistically indistinguishable from zero, with modest magnitudes and no discernible time trends. However, life satisfaction shows some pre-treatment variation. While no clear trend emerges, certain estimators (e.g., TWFE OLS and Borusyak et al. (2021)) detect statistical significance at the 5% level two years before treatment (year -2). Although other estimators (e.g., Callaway and Sant'Anna (2021) and De Chaisemartin and d'Haultfoeuille (2020)) do not, and the significance of a single period in a short pre-treatment span might not necessarily violate the no anticipation assumption. We discuss this issue in greater detail in a later section.



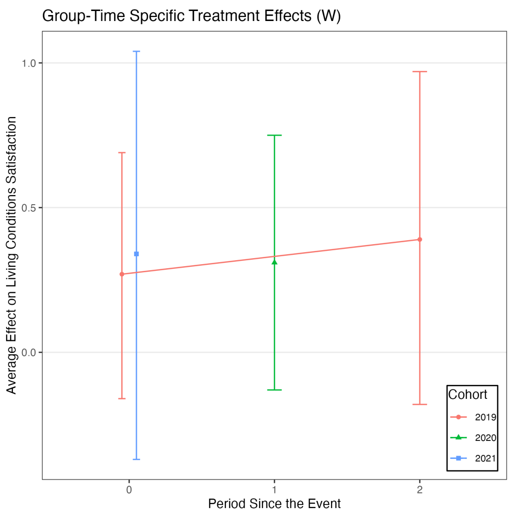
(a) Life satisfaction (CS)



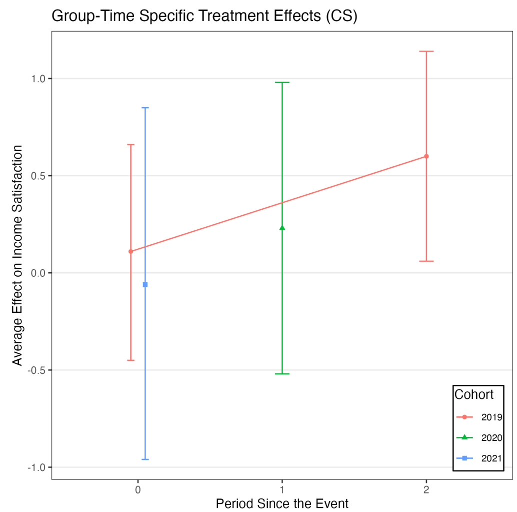
(b) Living conditions satisfaction (CS)



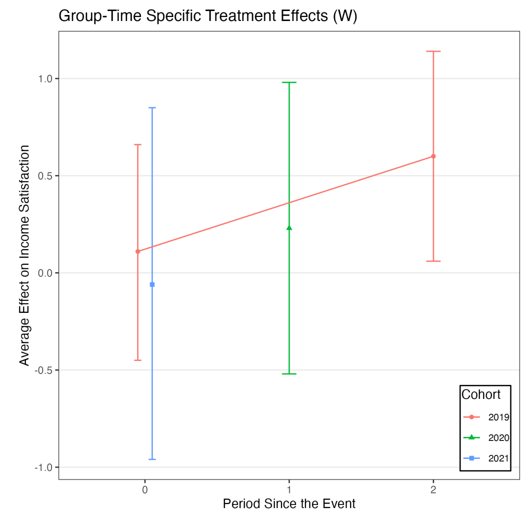
(c) Satisfaction with income(CS)



(d) Life satisfaction(W)



(e) Living conditions satisfaction(W)



(f) Satisfaction with income(W)

Figure 4.6: Group specific dynamic treatment effects of the *Clean Heating Policy* on subjective well-being. Figures in the first row are the group-time specific estimates stimated with Callaway and Sant'Anna (2021)(CS), while figures in the second row are estimated with the method of Wooldridge (2021)(W). Different colors of the dots and lines represent different cohorts that got the treatment of the *Clean Heating Policy* in varying years with red (2019), green (2020), and blue (2021). The intervals are the 95 percent confidence intervals based on standard errors clustered at the village level.

4.4.2 Heterogeneity analysis

Households with varying characteristics may experience different impacts from the *Clean Heating Policy* on subjective well-being. This section analyzes heterogeneous treatment effects to explore how specific groups benefit or are disadvantaged by the intervention. We categorize households based on baseline characteristics (e.g., age of the survey participant, wealth index) and estimate the heterogeneous treatment effects using Equation 4.3. Figure 4.7 illustrates these effects on life satisfaction and satisfaction with living conditions across different subgroups. Naturally, splitting up estimated effects across sample subgroups can reduce the precision of each estimate, as compared with the pooled results presented earlier.

By age of the health survey participant. Given the demographic composition of rural Beijing households, the age of the health survey participant can serve as a proxy for household characteristics. Figure 4.7a presents the heterogeneous impacts of the *Clean Heating Policy* on life satisfaction across age groups. Younger households exhibit significantly greater positive impacts compared to those aged 70 or older, who experience a non-significant negative impact. Limited income sources and reliance on government pensions among older adults may exacerbate the financial burden of increased heating costs, potentially outweighing the policy's environmental and health benefits. Additionally, adapting to new technologies associated with clean heating may disrupt traditional lifestyle habits for this demographic, such as sleeping on a kang.[14]

By wealth index. Figure 4.7b illustrates the heterogeneous impacts of the *Clean Heating Policy* on life satisfaction across baseline wealth index groups. The wealth index, constructed using principal component analysis of socioeconomic characteristics (e.g., housing, appliances, land), provides a more comprehensive measure of household economic status than income alone (X. Li et al., 2022). While there is a weak positive correlation between the wealth index and life satisfaction impacts, only the top wealth quintile shows a substantial and statistically significant positive effect (0.58). Lower wealth quintiles exhibit smaller, non-significant impacts. This suggests that households with higher socioeconomic status,

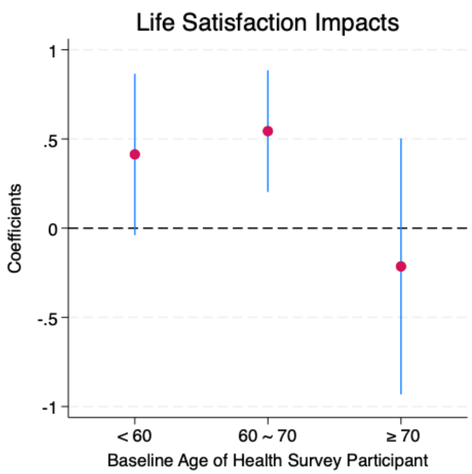
[14] A kang is a brick bed heated by internal hot smoke from burning firewood or coal.

facing less financial pressure and potentially having greater aspirations for improved living conditions, are more likely to perceive the benefits of the policy.

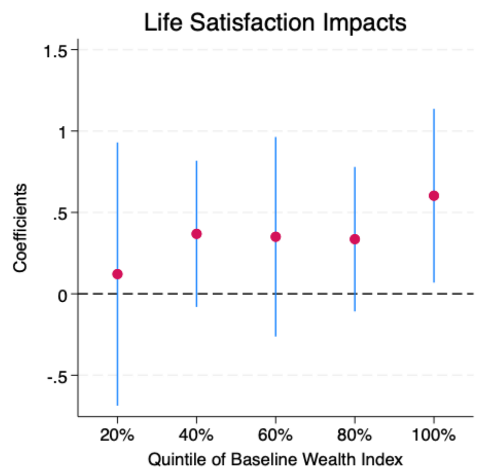
By self-reported health status. We categorized households into three health groups based on the self-reported health status of health survey participants at baseline, relative to their peers: excellent/good, fair, and poor. Due to a limited number of responses in the "excellent" category, we combined it with the "good" category. A negative correlation emerged between self-reported health and life satisfaction impacts as shown in Figure 4.7c. Households with a family member reporting fair or poor health experienced significantly positive gains in life satisfaction from the *Clean Heating Policy*, while those in good health showed likely smaller effects. The policy's provision of a healthier living environment (e.g., air source heat pumps offering stable indoor temperatures and cleaner air) and the reduction in physical burdens associated with solid fuel use (e.g., collecting firewood and frequently adding briquettes to stoves) likely contributed to an improved quality of life for those in poorer health.

By baseline indoor temperature. Figure 4.7d reveals a U-shaped relationship between baseline indoor temperature and the impact of the *Clean Heating Policy* on satisfaction with living conditions. Households with middle-range temperatures experienced minimal effects, whereas those with the lowest and highest baseline temperatures exhibited greater positive impacts. However, the drivers of these impacts may differ. Households with initially low indoor temperatures likely benefited primarily from improved space heating, leading to higher indoor temperatures. In contrast, households with high baseline temperatures, often achieved through burning more solid fuels, may have experienced greater improvements in environmental quality, such as increased indoor cleanliness and better air quality, due to reduced solid fuel combustion.

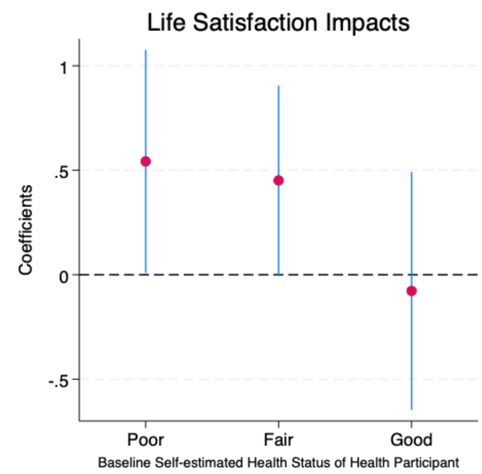
By baseline personal exposure to $PM_{2.5}$. Figure 4.7e reveals a weak positive correlation between baseline personal 24-hour $PM_{2.5}$ exposure and the impact of the *Clean Heating Policy* on satisfaction with living conditions. While households in the top two $PM_{2.5}$ exposure quartiles exhibit slightly larger positive effects, those in the bottom two quartiles show minimal impact. However, this relationship may be confounded by factors influencing personal $PM_{2.5}$ exposure beyond fuel use, such as smoking, activity patterns, and outdoor air quality. Studies have shown that natural gas users can experience higher $PM_{2.5}$ exposure compared to coal users (X. Li et al., 2021). Consequently, higher personal $PM_{2.5}$ levels do not necessarily indicate greater reliance on solid fuels or greater improvement in air quality as a result of the *Clean Heating Policy*.



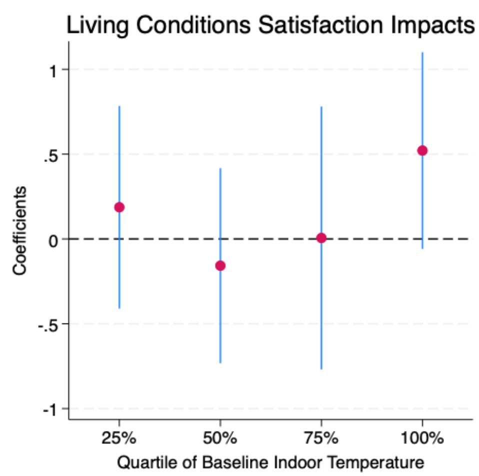
(a) Life satisfaction–age



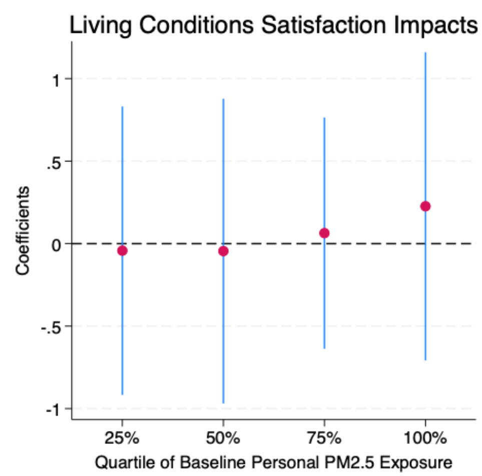
(b) Life satisfaction–wealth



(c) Life satisfaction–health



(d) Satisfaction with living conditions–temperature



(e) Satisfaction with living conditions–air quality

Figure 4.7: Heterogeneous treatment effects of subgroup of households.

4.4.3 Mediation analysis of life satisfaction impacts

To further explore the mechanisms underlying the policy's impact on subjective well-being, we conducted a bootstrap mediation analysis. This involved constructing 500 bootstrap subsamples through random resampling with replacement and estimating indirect effects for each subsample (Dumitrache et al., 2015; Preacher & Hayes, 2008). The 95% confidence intervals for the mediation effect were established by identifying the 2.5th and 97.5th percentiles of these estimates (Wen & Liu, 2020, p.92).

Figure 4.8 presents the results of the bootstrap mediation analysis for life satisfaction. The left and right panels display 95% confidence intervals for indirect and direct effects, respectively. Mediators include household winter energy expenditure, winter nighttime indoor temperature, 24-hour personal $PM_{2.5}$ exposure, sleep hours of health survey participants, and weekly guest visits, representing well-being domains such as wealth status, living environment, health, and social capital. Apart from indoor temperature, the indirect effects of other mediators are negligible and statistically insignificant, suggesting a weak relationship between these variables and the overall treatment effect. The mediation effect of indoor temperature contributes to only about 5% of the total impact on life satisfaction.

We further included satisfaction with well-being domains — specifically, satisfaction with living conditions and satisfaction with income — as additional mediators. As shown in the last two rows of Figure 4.8, although not statistically significant at the 95% level, the indirect effect through satisfaction with living conditions is numerically substantial, accounting for approximately 30% of the total treatment effect on life satisfaction. This suggests that improvements in living conditions play a key role in policy's impact on overall well-being.

The observed weak mediation effects warrant careful interpretation. While the selected mediators represent key well-being domains, their limited explanatory power does not diminish the importance of these domains in the overall well-being impacts. For example, sleep hours, a proxy for health, may still significantly influence well-being despite the non-significant mediation effect, given the study's short timeframe, which limits our ability to capture long-term impacts, especially in health. The policy likely affects well-being through improvements in other health outcomes as well. Moreover, the substantial direct effect suggests that unmeasured factors, such as time savings and increased safety, may significantly contribute to the policy's influence on life satisfaction.

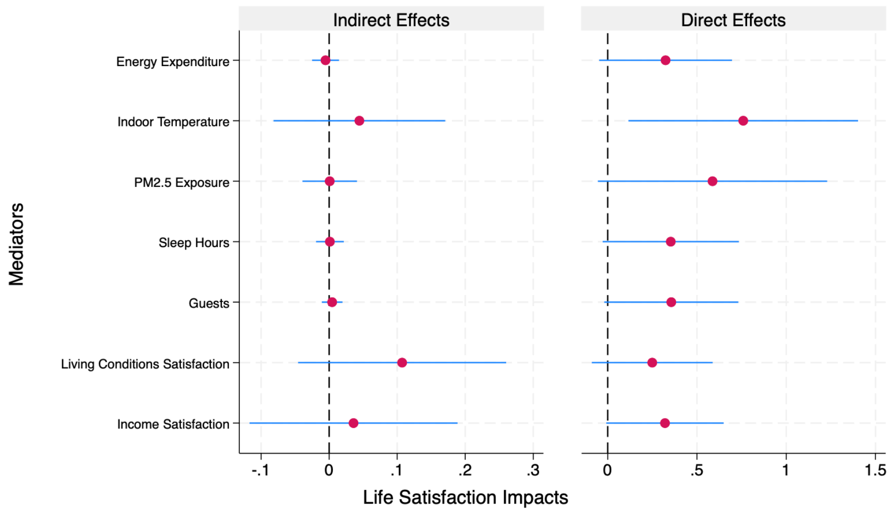


Figure 4.8: Mediation analysis of life satisfaction impacts. The indirect and direct effects in a row were derived from a single bootstrapping analysis for each mediator. Please note that the scale of the x-axis differs between indirect and direct effect plots. Differences in the total treatment effects, i.e., the sum of indirect and direct effects, across separate mediation analyses are due to differences in the samples. For example, we have only about 1300 observations for indoor temperature and personal exposure to $PM_{2.5}$ mediators.

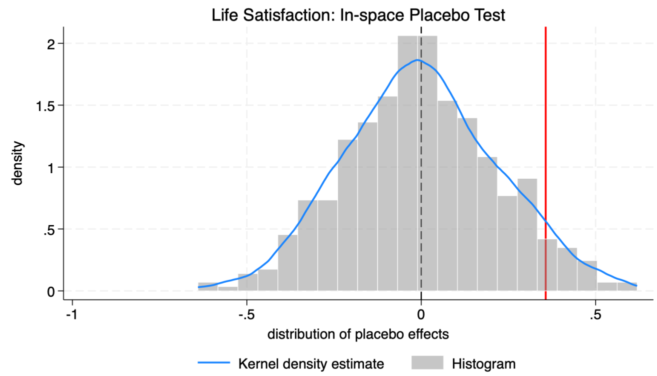
4.4.4 Robustness analysis

In this section, we assess the robustness of our estimates through placebo tests and address potential uncertainties stemming from the observations in Fangshan district.

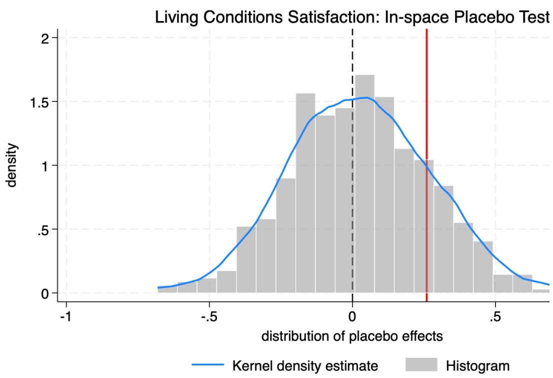
4.4.4.1 Placebo test

The placebo tests aim to verify the causal interpretation of our estimated subjective well-being effects, ensuring they are attributable to the *Clean Heating Policy* rather than confounding factors. We conducted two types of placebo tests: (1) In-space placebo test: The full sample of N households was divided into G groups according to the timing of their treatment (t_g), with N_g households in each group. First, N_1 households were randomly selected as "treated" at t_1. Then, from the remaining $N - N_1$ households, N_2 households were randomly selected as "treated" at t_2, and so forth. The main regression analysis was conducted using this modified dataset. We repeated the in-space placebo test 500 times. (2) In-time placebo test: For treated households, the treatment timing was artificially advanced by one or two years, and post-treatment observations were excluded. Both tests were implemented using the "didplacebo" Stata package (Chen et al., 2023). Additionally, we conducted a "mixed" placebo test, combining the in-space and in-time placebo tests, also with "didplacebo" package. The results are available in Figure C.3 in the appendix.

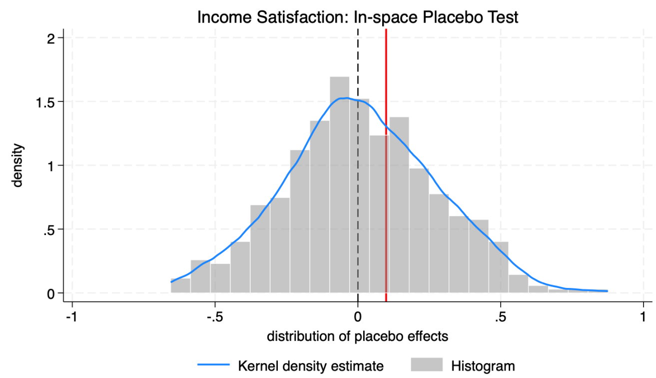
Figure 4.9 displays the results of 500 in-space placebo tests, which approximate a normal distribution centered around zero. This suggests that our baseline life satisfaction estimate, significant at the 5% level, is unlikely to be driven by confounding factors. As visualized by the red vertical line in Figure 4.9a, the estimate falls within the right tail of the distribution, with only 10% of placebo estimates exceeding its absolute value.



(a) Life satisfaction



(b) Satisfaction with living conditions



(c) Satisfaction with income

Figure 4.9: In-space placebo test of subjective well-being impacts. This figure shows the in-space placebo test results on (a) life satisfaction, (b) satisfaction with living conditions, and (c) satisfaction with income by randomly determining the treatment status across households. The gray bars and blue lines illustrate the distribution of 500 estimates of Equation 4.1 using Monte Carlo analysis draws for "fake" treatment status. The red vertical lines represent the main estimation results based on the treatment status in reality.

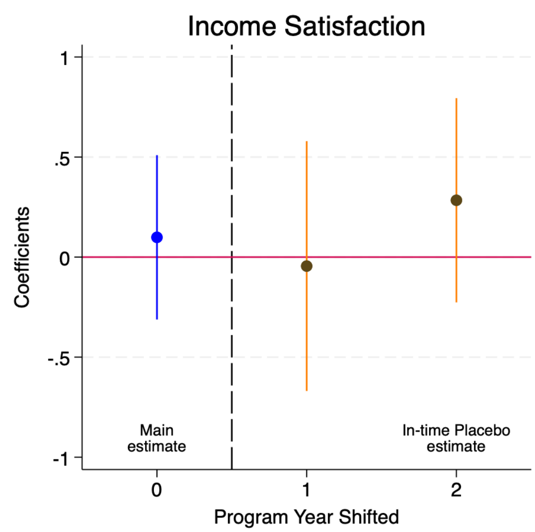
Figure 4.10 displays the results of the in-time placebo test, where the treatment timing is artificially advanced by one or two years. For satisfaction with living conditions (Figure 4.10b) and income (Figure 4.10c), the resulting estimates are small and statistically insignificant. However, life satisfaction shows a significant in-time placebo effect (Figure 4.10a), potentially indicative of anticipation effects, where the treatment impacts well-being before its actual implementation (Roth et al., 2023). Specifically, the findings suggest that households experience a negative impact on life satisfaction two years prior and a positive impact one year prior to receiving the *Clean Heating Policy*.

Rather than reflecting true anticipation, the observed pre-treatment effects on life satisfaction may be due to response patterns. The cognitive challenge of quantifying life satisfaction on a short-term basis might lead respondents, particularly among older and less educated individuals, to simplify their answers into a three-point scale (top, medium, and bottom) (Barrington-Leigh, 2024). As shown in Figure C.4 in the appendix, the distribution of life satisfaction among untreated households is severely left-skewed, with over 40% of respondents in the final wave selecting the top option. This unusually high proportion of "completely satisfied" in the final wave might be exacerbated by the sensitive nature of the life satisfaction question during COVID-19 restrictions or the anticipation of a lifting of strict quarantine policies.

To address potential response bias, we re-estimated the main regression and in-time placebo tests, excluding all observations with "ten out of ten" as the response to the life satisfaction question. As demonstrated in Figure C.5 in the appendix, the main effect remains consistent (0.34, 95% CI: 0.01–0.67), while in-time placebo tests become insignificant. The less pronounced in-time placebo effects observed for satisfaction with living conditions and satisfaction with income, which were asked subsequent to life satisfaction in the survey, further support the hypothesis of response bias affecting the life satisfaction measure.

(a) Life satisfaction

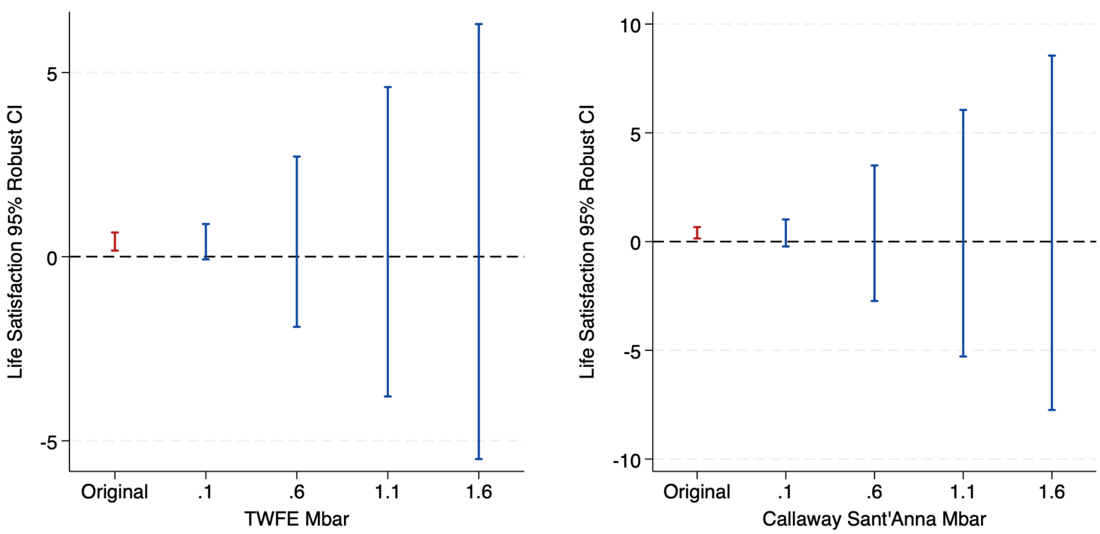
(b) Satisfaction with living conditions



(c) Satisfaction with income

Figure 4.10: In-time placebo test of subjective well-being impacts. This figure shows the in-time placebo test results on (a) life satisfaction, (b) satisfaction with living conditions, (c) satisfaction with income by shifting the actual treatment timing by one or two years in advance. The x-axis indicates the years of the treatment timing shifted with 0 represent the treatment year in reality. The blue line with the circle markers to the left of the dashed vertical line is the main estimations while the yellow lines with the circle markers to the right of the dashed vertical line are the in-time placebo estimations. The intervals are the 95 percent confidence intervals based on standard errors clustered at the village level.

Given the event study and in-time placebo test findings on life satisfaction, we conducted a formal sensitivity analysis using "HonestDiD" (Rambachan & Roth, 2023), as suggested by Roth et al. (2023), to assess the robustness of our results to potential parallel trend violations. Figure 4.11 presents "HonestDiD" estimates using both TWFE and Callaway and Sant'Anna (2021) estimators. The breakdown value ($\bar{M}$) of approximately 0.1 indicates that the statistical significance of our main life satisfaction estimate is robust to parallel trend violations only up to 10% of the maximum pre-treatment deviation. Given the sensitivity of the average life satisfaction impact to the parallel trend assumption, its statistical significance should be interpreted cautiously.



(a) Honest TWFE DiD **(b)** Honest Callaway and Sant'Anna DiD

Figure 4.11: "Honest DiD" of the average treatment effects on life satisfaction.

4.4.4.2 Uncertainty of Fangshan observations

Due to the unique characteristics of observations in Fangshan district, their inclusion might impact the robustness of our findings. First, lack of implementation of the *Clean Heating Policy* in Fangshan sample villages during the study period due to inadequate capacity of the electrical infrastructure renders all its observations control units in DiD analysis. Second, a substantial briquette price increase occurred only in Fangshan during the final wave, potentially affecting the parallel trend assumption. To assess this, we replicated the baseline regression excluding Fangshan observations entirely (NFS) or only those from the final wave (NFS4). Table 4.3 presents the results. Despite these sample variations, the estimated treatment effects remain consistent in magnitude and statistical significance, particularly between the full sample and NFS results. This suggests that including Fangshan observations has limited impact on our overall findings.

Table 4.3: Robustness check of observations of Fangshan. Each column of estimate is from a separate regression based on the different dataset. Specifically, the "Baseline" columns are identical to our preferable specification with the full observations as shown in Table 4.2. The "NFS4" columns are based on the subset of the dataset by removing observations of Fangshan in the last season. The "NFS" columns are based on the subset of the dataset by removing all observations from Fangshan. Standard errors in parentheses are clustered at the village level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Life satisfaction			Satisfaction with living conditions			Satisfaction with income		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Baseline	NFS4	NFS	Baseline	NFS4	NFS	Baseline	NFS4	NFS
Treat	0.36**	0.28*	0.38**	0.26*	0.18	0.28	0.10	0.05	0.11
	(0.14)	(0.15)	(0.15)	(0.14)	(0.17)	(0.17)	(0.20)	(0.21)	(0.21)
Num.Obs.	2789	2555	2185	2789	2555	2185	2789	2555	2185
R^2	0.56	0.58	0.56	0.54	0.56	0.54	0.58	0.60	0.59
Household fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓

4.5 Conclusion and discussion

This paper evaluates the impact of China's *Clean Heating Policy*, a large-scale intervention aimed at transitioning rural households to cleaner heating solutions, on subjective well-being. By leveraging firsthand survey data from over 1,000 households across 50 Beijing villages from 2018 to 2021, we estimate the average treatment effects on life satisfaction, satisfaction with living conditions, and satisfactions with income. In addition to assessing aggregate impacts, we explore heterogeneity in effects based on baseline socioeconomic characteristics and environmental conditions. Our findings reveal that the policy significantly increased life satisfaction by 0.36 (95% CI: 0.09–0.63) points on a 0–10 scale, with comparatively smaller effects on satisfaction with living conditions and satisfaction with income. Notably, the greater gains in life satisfaction were observed among younger households, those with higher wealth status, and those including members in poor health.

Our simple mediation analysis reveals weak treatment effects associated with quantified mediating variables like energy expenditures, air quality, indoor temperature, and sleep duration. This suggests that the policy's impact on well-being likely stems from unmeasured factors, such as time and labor savings from reduced fuel use and enhanced safety. Our preliminary exploration sheds light on the potential gap between the intervention objectives and the household's priorities. The study did not allow for a deeper identification of mediation pathways. Future research should investigate household-prioritized energy transition impacts to inform policy and improve the current dismal situation where the global household energy transition is seriously lagging behind.

Our study has several limitations. First, the focus on Beijing, a relatively affluent region with substantial clean heating subsidies, might limit the generalizability of our findings to other rural areas. Reports of households reverting to solid fuel use or suffering freezing due to insufficient supply or affordability underscore the potential heterogeneity of policy impacts. Second, the two-year study period might not fully capture long-term well-being effects, which are crucial for assessing the policy's sustainability. Finally, shock impacts of the COVID pandemic on people's subjective well-being warrant further investigation.

The COVID pandemic hit the entire world midway through our study. The consequences of epidemics such as quarantine and health damages are thought to have a large effect on people's subjective well-being (O'Connor et al., 2021). Our study design assumes that factors other than the *Clean Heating Policy* affect the subjective well-being of the sample families in the different treatment groups in the same way, but how a major shock such as an epidemic interferes with such an assumption is difficult to quantify.

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Chapter 5

Discussion

5.1 Overview

This dissertation explores the issue of rural household energy transition in China from an interdisciplinary perspective. I start by examining the temporal trends and spatial characteristics of the transition at the national and provincial level over the past three decades, and forecast a "business as usual" scenario up to 2050 using administrative statistics (**Chapter 2**). Subsequently, employing first-hand survey data from over 1000 rural households collected between 2018 and 2022 in Beijing, I evaluate the impacts of the *Clean Heating Policy* on household energy poverty (**Chapter 3**) and subjective well-being (**Chapter 4**). This dissertation is a quantitative study that primarily employs methods such as causal inference based on quasi-natural experiments, time series analysis, and mediation effect analysis. In this discussion chapter, I synthesize the key findings from each chapter in Section 5.2, discuss further thoughts and the limitations of this study in Section 5.3, and propose several directions for future research in Section 5.4.

5.2 Key findings

This section synthesizes the key findings from each manuscript.

5.2.1 Spatial disparities of China's rural household energy transition

In addressing environmental, health, and other social challenges associated with household solid fuel use, transitioning to modern energy sources has emerged as a global development goal (McCollum et al., 2017). However, the sluggish pace of this transition in most developing countries significantly jeopardizes the feasibility of achieving SDG 7 — ensuring access to affordable, reliable, sustainable and modern energy for all — by 2030 (IEA, 2023). Accelerating this transition through targeted interventions has become a prevalent international effort (Quinn et al., 2018). In North China, once known for its severe winter air pollution, targeted interventions aimed at reducing coal-burning for space heating in rural households are crucial (J. Liu et al., 2016). A pivotal question arises before exploring potential interventions: what would the situation look like without any interventions? This question is essential as it not only justifies the necessity of any planned interventions but also provides a counterfactual to assess their effectiveness. In **Chapter 2**, I address this by analyzing historical administrative statistics on rural household energy consumption, setting the stage for evaluating the impact of the *Clean Heating Policy* in subsequent chapters.

The results show that at the national level, China's rural household sector has undergone a gradual energy transition over the past 30 years. Socio-economic developments have spurred a rapid increase in per capita energy consumption in rural Chinese households, particularly electricity. By 2013, China was providing all 1.4 billion people access to electricity for daily use (IEA, 2023). The rise in modern energy's share within total energy consumption signals an ongoing transition from traditional biomass and coal to modern energy sources. Between 1991 and 2018, China's rural household energy transition experienced a decade of stagnation, followed by a decade of rapid commodification marked by a swift decline in biomass fuel use, and a clean transition phase since 2015.

This transition, however, displays significant spatial disparities. While national-level analysis shows a rapid decline in biomass fuel consumption accompanied by a surge in modern energy use, an alarming trend is the rising per capita coal consumption, mainly used for heating, suggesting an inconsistent transition between cooking and heating in rural households. A provincial-level analysis within the China Rural Domestic Energy Use Zone framework sheds further light on this hypothesis. Results indicate that provinces in the WW-S and CW-YP zones, which have less intense winter heating needs, have advanced more in the energy transition compared to those in the EC-NE and EC-NW zones, where heating demands are more substantial. Moreover, a simple two-way fixed effects model using per capita income as an independent variable reveals a weak correlation between income increases and clean energy share in colder regions. These findings highlight significant challenges associated with energy transitions in rural household space heating.

Considering these challenges, what would the future timeline look like for energy transition under a "business as usual" scenario? Using an autoregressive integrated moving average (ARIMA) model, our forecasts show that while provinces with less intensive heating needs might achieve a complete transition, the share of clean energy in colder regions will likely remain below 50% by 2050. Thus, implementing a large-scale intervention targeting rural household energy use for space heating is imperative to meet China's air quality and climate goals. An analysis comparing actual and predicted clean energy proportions in three North Chinese provinces from 2015 to 2018 highlights the significant impact of the *Clean Heating Policy* in accelerating the rural heating energy transition.

5.2.2 Significant enhancements in rural household heating via the *Clean Heating Policy* with minimal financial impact

The *Clean Heating Policy*, while facilitating the transition, is estimated to generate positive net benefits for northern China by improving air quality and reducing health damages (Ma et al., 2023; X. Zhang et al., 2019). However, an important concern in implementing the *Clean Heating Policy* is the financial burden it places on economically disadvantaged rural households. This raises the question of whether the *Clean Heating Policy* might render adequate heating unaffordable for these households, thereby creating or worsening a condition of energy poverty. In **Chapter 3**, we apply the difference-in-differences method to our first-hand survey data to evaluate the impact of the *Clean Heating Policy* on various measures of energy poverty.

The baseline regression results suggest that the *Clean Heating Policy* markedly improves space heating for rural households with minimal financial impacts. Prior to the implementation of the *Clean Heating Policy*, the majority of sampled households could be considered to be in energy poverty, as over 10% of their family income was allocated to winter energy expenses. Furthermore, the space heating — indicated by indoor temperature and the proportion of houses with regular heating — was inferior. The *Clean Heating Policy* has effectively raised the average nighttime indoor temperature by 1.8°C and added 1.4 more rooms with regular heating, while only adding approximately 2% to the family's annual income dedicated to winter energy expenditure. These findings underscore the crucial role of government "triple" subsidies on electricity tariffs in alleviating the financial burden of rural households during the energy transition. Additionally, the widespread adoption and expansion of the central water radiator system, as facilitated by the *Clean Heating Policy*, has significantly enhanced space heating. The contrasting results obtained from economic measurements and space heating measurements of energy poverty underscore the limitations of traditional economic indicators, which rely solely on energy expenditure as a percentage of household income. This highlights the importance of focusing on the degree of satisfaction of energy needs when addressing energy poverty.

We further explore the heterogeneity in treatment effects, taking into account the duration of treatment exposure and household baseline characteristics. The results from the event study suggest that the positive impacts of the *Clean Heating Policy* on economic and space heating outcomes are sustained for at least two years post-treatment. These constant impacts are likely dependent on ongoing government subsidies and guidance regarding the use of air source heat pumps. Moreover, the treatment effects vary among households based on their characteristics. Those residing in high-altitude villages, lacking radiator systems, and with lower wealth at baseline experience greater financial challenges under the *Clean Heating Policy*. Consequently, additional support is essential for economically disadvantaged households in colder climates, especially when the *Clean Heating Policy* is implemented in less developed extreme cold provinces.

Our simulations under various government subsidy scenarios reveal that future reductions in the government's subsidy could impose significant financial burdens to rural households. This aligns with observations from other provinces, where lower subsidies and income levels contribute to inadequate heating, eventually leading to the abandonment of clean heating solutions and a resurgence in the use of solid fuels (S. Xu & Ge, 2020). In provinces outside Beijing, the *Clean Heating Policy* is currently caught in a bind: the government struggles to sustain subsidies, and residents find clean heating unaffordable (Z. Zhang et al., 2021). Between 2017 and 2018, local governments expended over 50 billion RMB in a year on subsidies for clean heating, yet the issue of affordability persists (Y. Zhu & Yu, 2019). Developing subsidy policies that support sustainable clean heating without financially burdening both government and households remains a significant challenge (M. Li et al., 2021; Meng et al., 2023).

5.2.3 The *Clean Heating Policy* has improved overall life satisfaction

Spontaneous energy transitions occur when the perceived benefits of clean energy, including improved health, better environmental aesthetics, and less work time lost, outweigh the marginal costs of time, materials, and knowledge investments (Greenstone & Jack, 2015; Hanna & Oliva, 2015; Pattanayak & Pfaff, 2009). Thus, it is reasonable to infer that a household's decision to make such transitions would likely enhance its welfare. Although results from **Chapter 3** show that households in the *Clean Heating Policy* incur slightly higher expenses for significantly improved space heating, the mandatory nature of the transition and its extensive impacts on aspects beyond economics and thermal comfort leave the effect on quality of life unsolved. To further explore this, **Chapter 4** presents empirical evidence of the *Clean Heating Policy*'s impacts on subjective well-being.

We use the difference-in-differences method to examine the overall impact on subjective well-being through life satisfaction measurements, as well as the impacts on two important domains of satisfaction, the satisfaction with living conditions and satisfaction with income. Our baseline regression results indicate that the *Clean Heating Policy* significantly enhances life satisfaction by approximately 0.36 (95% CI: 0.09–0.60) on a 0–10 scale, an effect comparable to more than doubling family income. However, the effects on living conditions satisfaction and family income satisfaction are less pronounced. Specifically, the negligible impact on income satisfaction aligns with the minimal financial burdens observed in **Chapter 3**.

The analysis of heterogeneous treatment effects identifies which households are better or worse off from the *Clean Heating Policy*, providing some insights into the mechanisms affecting well-being. Results indicate that wealthier households, as well as those with younger or less healthy members, tend to feel they benefit more from the *Clean Heating Policy*. These observations suggest that financial and health aspects may be crucial in how the *Clean Heating Policy* influences subjective well-being. Our preliminary exploration of mechanisms through mediation analysis indicates that the indirect effects mediated by selected factors such as winter energy expenditure, nighttime indoor temperature, $PM_{2.5}$ exposure, sleep duration, and guest visits contribute minimally to the overall effects.

It should be emphasized that these results depend heavily on the choice of mediators, which means that the lack of a significant mediation effect of certain selected factors does not mean that the *Clean Heating Policy* will not affect people's well-being through these domains. For instance, although sleep duration, which we selected as a health indicator, was not a significant mediator, the *Clean Heating Policy* might still enhance well-being by improving other health outcomes. However, in the context of the *Clean Heating Policy*, the impact on subjective well-being through improved air quality might be less substantial than expected. This underscores a crucial policy insight: while the primary goal of most household energy transition interventions is to enhance air quality and reduce health risks, households may prioritize other factors in their energy use decisions, rather than perceiving significant improvements in their quality of life through these targeted benefits. Understanding user priorities in household energy decisions and promoting clean technologies that meet these needs is essential for a sustainable transition (M. Jeuland et al., 2015; Urmee & Gyamfi, 2014).

5.3 Further thoughts

In this section, I discuss some further thoughts on topics that were not covered in detail in the dissertation, as well as some limitations of the survey data used in the previous chapters.

5.3.1 Role of biomass fuels in household energy transition

This dissertation focuses on the coal-reducing space heating intervention in rural North China, with a lesser emphasis on other energy sources such as biomass fuels. However, it is crucial to recognize that biomass is the primary source of household energy in less developed countries, due to its unparalleled nature of being freely and easily available (Karekezi et al., 2006). Therefore, addressing the substitution or efficient utilization of biomass fuels is a critical aspect of the global household energy transition (Sagar & Kartha, 2007). In this section, we discuss the role of biomass fuels in household energy transition.

As we discussed in **Chapter 2**, the availability of information on non-commodity energy sources such as biomass (e.g., firewood and cow dung) in Chinese statistics is severely limited. Both the China Energy Statistics Yearbook and the China Rural Statistics Report, which are pivotal sources for domestic rural energy data in China, ceased publishing national/provincial level data on biomass fuels after 2008. Moreover, they never included energy sources like yak dung, which is crucial for rural households in the pastoral areas of Northwest China (Rhode et al., 2007). The primary challenge lies in the difficulty of accurately measuring the quantity of biomass fuel collected by households, unless it is done through a fuel-weighing campaign (Shen et al., 2022). Due to the lack of reliable statistical data, research on the energy transition in rural Chinese households face a significant challenge: biomass energy is widely used, yet its exact contribution to the energy mix remains unclear. In **Chapter 2**, we attempt to compensate for the lack of official statistics on biomass fuels by integrating data from various sources, yet there remains a risk that its share of total energy consumption is underestimated. A recent study utilizing a machine-learning-based geospatial model predicted that approximately 6.9 ± 2.6 giga-tons of coal equivalent in rural household biomass consumption were unaccounted for in China's energy statistics, representing about 15.9 ± 6.0 percent of China's final energy consumption (S. Wu et al., 2024).

The significant underestimation of biomass consumption carries important policy implications. First, considering that the emission factors of several pollutants from burning raw biomass fuel are higher than those from coal (Shen et al., 2010), it suggests that if the *Clean Heating Policy* focuses solely on reducing coal use, the expected improvements in both household and ambient air quality might be much lower than anticipated. Therefore, one issue is whether the *Clean Heating Policy* should also address biomass fuel use. In **Chapter 3**, we briefly explored the role of biomass in the *Clean Heating Policy.* On one hand, burning more biomass could be a coping strategy for households facing energy poverty under the policy. On the other, traditional heating practices like wood-burning kang are deeply ingrained, raising questions about their replacement by new clean heating technologies. Preliminary results shown in Figure 3.3a suggest that the *Clean Heating Policy* on average reduced the use of kang for heating, indicating that households could achieve adequate heating without additional biomass burning. This observation also suggests that coal-reduction policies could also substitute biomass fuel consumption, altering traditional energy use habits. However, interviews with village leaders suggest that completely replacing biomass burning without a further ban is unrealistic. Indeed, imposing further bans on biomass fuels could maximize the reduction of pollutant emissions from rural residents, but it would push low-income families into a more vulnerable situation. Should there be an unstable supply or price increase of modern energy sources, these families would have no alternative but to endure the cold. Therefore, managing the use of biomass fuels through education and guidance, rather than outright prohibition, could be a better approach in balancing policy effectiveness and household energy security.

Second, given the widespread use of biomass fuels, it is worth considering whether efficient utilization of biomass fuels could serve as another technological pathway for clean heating, in addition to electricity and natural gas, in some regions. In addition to Beijing-Tianjin-Hebei and surrounding areas, the Chinese government also has piloted the *Clean Heating Policy* in other northern provinces around 2018, particularly in the extremely cold regions of the Northeast and Northwest (Liang, 2019; The People's Government of Qinghai Province, 2018). Based on the significant discrepancies observed in households at different altitudes discussed in **Chapter 3**, a heavier financial burden can be expected for those living in provinces with extremely cold climates and less wealth. In recent years, technological approaches to clean heating in these provinces have expanded beyond simple *Coal to Natural Gas* and *Coal to Electricity* conversions. They now include locally adapted explorations of various clean energy sources such as biomass fuels, geothermal energy, and solar energy (National Development and Reform Commission & National Energy Administration, 2022). In areas rich in biomass resources, such as the northeast provinces, burning biomass pellets, which significantly reduce the pollutant emissions than raw biomass, can be used as a short-term transitional solution for households that cannot obtain or afford electricity or natural gas for heating (Carter et al., 2018; L. Zhang et al., 2024).

5.3.2 Field survey data limitations

Two chapters of this dissertation rely on survey data collected in the field. In this section, we will discuss the limitations associated with the survey data used.

Our observational data involve two levels in which selection occurs and bias may be introduced: the government's selection of villages to receive the *Clean Heating Policy* and the determination of the sample villages in the study design. Due to the government's lack of transparency in the criteria for implementing the *Clean Heating Policy* in villages, we face a significant challenge in causal inference. We are unable to fully control for confounding factors that influence both the treatment status of villages and the outcomes of interest in our DiD regressions. This dissertation tackles the challenge using a two-way fixed effects model that accounts for both time-invariant factors and time trends, supplemented by additional control variables to address potential time-varying confounding factors. The consistent results across various model specifications indicate that the government's selection criteria have minimal influence on our estimates.

Regarding the sampling strategy, conducting random sampling at the village level was impractical due to the challenge of fully assessing the policy's implementation across all villages in Beijing at the baseline. Although these 50 sample villages vary in terms of population size, per capita income, and other factors, the DiD identification strategy does not depend on baseline similarity. The pre-treatment results from the event study support the critical parallel trend assumption, which is foundational to the DiD analysis. However, concerns about the external validity of the results remain. The baseline survey, conducted in 2018 — three years after the *Clean Heating Policy*'s extensive implementation in Beijing — exclusively included villages that had not yet received the policy. Therefore, the results predominantly reflect conditions in Beijing's mountainous areas, rather than those of rural families in the plains of Beijing, who were among the early recipients of the policy.

The limited time span of our data restricts our ability to discuss the long-term impacts of the *Clean Heating Policy*. Continuous clean heating is a prerequisite for long-term effectiveness of the *Clean Heating Policy*. While this dissertation relies on panel data spanning four years from 2018 to 2022, our study design only allows us to examine the impacts of the *Clean Heating Policy* up to two years post-treatment. Even though the event study results suggested that the positive effects of the *Clean Heating Policy* persist in our study period, this duration is insufficient for understanding the sustained effects of the policy. This situation highlights the inherent challenges of causal inference in quasi-experimental studies. Quasi-experimental designs that rely on observational data often encounter difficulties in clearly defining interventions while also accommodating extended time scales. For instance, our dataset, which targets a specific policy, effectively identifies particular interventions but is constrained by its narrow temporal scope. Further efforts are needed to integrate complementary techniques to triangulate a long-run causal picture.

Additionally, the interruption of the data collection in 2021 due to COVID-19 complicates our ability to evaluate continuous dynamic treatment effects from cohorts treated early in the *Clean Heating Policy*. As a result, the dynamic treatment effects we estimate are based on different treatment cohorts, which makes it difficult to discern whether the temporal trends observed in the event study reflect actual dynamic treatment effects or merely cohort effects. This issue is particularly pronounced in the analysis presented in **Chapter 4**. The short coverage period also limits our ability to provide more robust support to the parallel trend assumption, as it restricts our capacity to evaluate pre-treatment estimates over extended time frames.

Many key variables in this study were self-reported by households, inevitably introducing measurement errors into the results. A significant concern in **Chapter 3** was the lack of accurate electricity expenditure data for all households. The households get the *Clean Heating Policy* treatment encountered a complex pricing structure of electricity, with a regular daytime price and a subsidized night-time valley price, complicating the estimation of electricity costs. Given that our survey participants are generally elderly, and some have their electricity bills managed by their children, this further complicates the estimation of expenditures. Efforts to gather electricity consumption data directly from household meters provided limited information, as the data did not cover the entire heating season, contributing little to improving data quality. Additionally, the "focal value rounding" phenomenon observed in the life satisfaction data in **Chapter 4** suggests cognitive challenges among the elderly rural population with limited formal education. The impact of these uncertainties on the results is discussed separately in the relevant chapters. After accounting for the impact of self-reported data on result uncertainty, the findings remained robust.

5.4 Future research

Building on the findings of this dissertation, I propose several ideas for future research.

5.4.1 Different types of policy instruments

Our results indicate that the *Clean Heating Policy* in Beijing, which combines command-and-control and price-type instruments, has effectively facilitated the energy transition for space heating at a cost that households could afford. However, this campaign-style energy transition, reliant on tight cooperation across various government levels and high subsidy rates, is underpinned by China's unique political context. For instance, ensuring that lower levels of government adhere to directives from higher authorities to fully implement a coal ban may prove challenging in other countries; in addition, the high financial subsidies involved may be unsustainable for other provinces in northern China or other developing countries. Considering the rise in briquette prices we observed in Fangshan District last season as an example: what are the differences between a purely price-based approach and the *Clean Heating Policy* in terms of their impact on the household energy mix and economic outcomes? More broadly, designing incentives to efficiently achieve household energy transitions across different political contexts remains a critical area for further exploration.

5.4.2 Household behavior in energy transitions

The outcomes of the *Clean Heating Policy* discussed in this dissertation reflect, to some extent, behaviors related to household heating, such as achieving better heating effects through the temperature settings of heat pumps. However, this dissertation provides less direct discussion of the broader behavioral impacts of the *Clean Heating Policy*. Has the energy transition prompted other behavioral changes? For instance, does the intervention in heating energy encourage a spontaneous transition in cooking energy? Will younger populations actively increase their labor supply to offset the financial burdens of the energy transition? The behavioral impacts resulting from the energy transition are still worth exploring.

5.4.3 Justice in energy transitions

Justice and equity issues are increasingly recognized as critical components of the energy transition. Carley and Konisky (2020) outlined four tenets of energy justice within this context: distributional justice, procedural justice, recognition justice, and restorative justice. This dissertation provides preliminary empirical evidence concerning distributional justice. For example, through the *Clean Heating Policy*, low-socioeconomic households gained access to modern, clean heating but also faced greater financial challenges compared to other treated households. Focusing solely on distributional justice, several unresolved issues remain. Questions arise regarding the equity of the current uniform subsidy approach and whether a more refined subsidy mechanism could improve the distributional justice. Additionally, the issue of distributional justice between urban Beijing beneficiaries and rural cost-bearers in the *Clean Heating Policy* warrants further exploration. Concerning other dimensions of justice, for example, how could households participate in the decision-making process of the *Clean Heating Policy* through the village committee is crucial for ensuring procedural justice. Future studies should examine these other dimensions of energy justice to promote a just and sustainable energy transition.

Chapter 6

Conclusion

The primary objective of this dissertation is to gain a better understanding of the impacts of household energy transitions driven by large-scale interventions. Through the analysis of administrative statistics on rural households' energy consumption in China, **Chapter 2** revealed that as socioeconomic conditions improve, households in regions with better socioeconomic status and mild energy demands tend to make progress in transitioning to cleaner energy sources. However, in areas with high energy demands, such as cold regions with intensive space heating needs, natural energy transitions without incentives are particularly challenging.

To address the developmental obstacles caused by solid fuel combustion and to meet the urgent need for climate change mitigation, large-scale interventions targeting household energy transitions are essential. While transitioning to modern energy sources can benefit households in various ways — such as improving their living environment, enhancing health, and saving time — it may also impose financial burdens and disrupt long-established habits.

Using the *Clean Heating Policy* in rural northern China as a case study, **Chapters 3** and **4** employed difference-in-differences methods to evaluate the impact of household energy transition interventions on energy poverty and subjective well-being. Our findings suggest that the *Clean Heating Policy* effectively facilitates the energy transition by improving household space heating with minimal financial costs and enhanced life satisfaction.

The *Clean Heating Policy* has achieved positive outcomes through a series of government regulations and economic incentives. The findings of this dissertation underscore the significant potential of well-designed interventions, which by providing long-term, sustained, and multifaceted support — ensuring the availability of new technology, affordability of modern energy, stability of energy supply, and reliable equipment operation — could effectively address the challenges of household energy transition faced by many developing countries today.

Appendix A

Appendix to Chapter 2

A.1 Characteristics of China for rural domestic energy use zones

The 31 provincial administrative regions of mainland China, including provinces, autonomous regions, and municipalities, have been divided into seven domestic energy use zones using a layer overlay approach (Station of Agricultural Ecology and Resource Conservation, 2019).This approach integrates China's Agricultural Climate Zoning, Building Climate Planning, China Rural Energy Comprehensive Zoning, and Rural Renewable Energy Zoning. For uniformity, we will refer to all provincial administrative units as "provinces" throughout this text. Table A.1 shows the components, land area, population, climate characteristics, and heating durations of these seven rural domestic energy use zones.

Among the seven zones, the Cold Winter-Yangtze Plain (CW-YP) encompasses the largest number of provinces, with nine, while the Cold-Tibet Plateau zone (C-T) only has two provinces. Significant differences in population density exist among these seven zones. The Cold-North (C-N) zone has the highest population density of 921 people/km^2, while the C-T zone has the lowest population density of 5 people/km^2. This is mainly due to the high altitude of the plateau area, which is largely unsuitable for living and production activities.

Except for C-N, the urbanization rates of the other districts are similar, with the shares of rural population in the total population ranging between 38% and 58%.

The most significant differences among these zones are the climate conditions and corresponding heating duration. Provinces in the Extreme Cold and Cold zones have long winter days below 0°C for at least two months, resulting in a long heating duration. The heating season can last for half a year in Extreme Cold provinces. Only a few provinces in CW-YP have mild heating needs around January. As for the Warm Winter-South (WW-S) provinces, there is no need for space heating in winter.

The difference in climate conditions and heating needs determines the energy use pattern for different domestic energy use zones. The difference in the proportion of rural household energy used for cooking and heating in the north (EC and C provinces) and south (CW, WW-S, and M-SW provinces) of China is significant. Specifically, the proportion of heating use in north China is as high as 63.1%, while in south China, it is only 22.6% (Zheng & Wei, 2019).

Table A.1: Characteristics of rural domestic energy use zones. The data were sourced from the Station of Agricultural Ecology and Resource Conservation (Station of Agricultural Ecology and Resource Conservation, 2019) and the Energy and Environment Research Department of the National Engineering Research Center for Housing and Living Environment of China (Energy and Environment Research Department, National Engineering Research Center for Housing and Living Environment of China, 2012). The population and rural population data are on the 2016 level.

Zone	Abbreviation	Provinces	Land Area (10,000 km^2)	Population (million)	Rural Population (million)	Heating Duration (months)	Accumulated Temperature greater than 0°C (°C)	Other
Extreme Cold-Northeast	EC-NE	Heilongjiang, Jilin, Liaoning	79.18	109.47	42.32	5∼6	<3600	<0°C, 130∼190 days
Extreme Cold-Northwest	EC-NW	Inner Mongolia, Ningxia, Xinjiang, Gansu, Shaanxi	347.19	119.31	57.66	4∼5	2100∼5700	<0°C, 120∼160 days
Cold-North	C-N	Beijing, Tianjin, Hebei, Shandong, Shanxi, Henan	69.61	641.34	150.94	2∼4	3900∼5300	<0°C, 50∼130 days
Cold-Tibet Plateau	C-T	Qinghai, Tibet	191.96	9.12	5.27	3	<500	<0°C, 80∼200 days
Cold Winter-Yangtze Plain	CW-YP	Shanghai, Jiangsu, Anhui, Zhejiang, Jiangxi, Hunan, Hubei,Sichuan, Chongqing	149.15	392.74	159.7	2∼3	5500∼7000	Mild heating needs around January
Warm Winter-South	WW-S	Fujian, Guangdong, Guangxi, Hainan	57.67	203.95	77.78	0	>7000	Basically no winter
Mild-Southwest	M-SW	Yunnan, Guizhou	55.93	194.92	102.03	0	5900∼6500	Minimum temperature $-5 \sim 0$°C, heating needs in alpine regions

A.2 Descriptive statistics of variables used in the two-way fixed effects model

Supplementary Table A.2 presents descriptive statistics of the dependent variable, which is the share of clean energy in rural household energy consumption, and the independent variable, which is per capita income, for seven different rural domestic energy use zones. However, due to only having two provinces in the C-T zone and missing values for Tibet, we were only able to obtain 14 observations, which may introduce some uncertainty in the following regression model. Over the 1991–2018 period, the proportion of clean energy in rural household energy consumption varied across the different zones, with an average range of 7.3% to 22.4%. The C-T zone had the lowest clean energy rate among all zones. Notably, significant progress in the rural household energy transition was observed in CW-YP, WW-S, and C-N zones during this period, where the dependent variable ranged from a minimum of 1% to a maximum of over 80%. Conversely, the process was comparatively slower in the C-T zone, where the maximum value of the dependent variable was less than 20%. In the last 30 years, per capita annual income has experienced significant growth in line with socioeconomic development, ranging from 2,500 to 5,000 RMB across distinct domestic energy use zones. In addition, there were observable differences in social development levels between regions, with CW-YP and C-N zones exhibiting higher per capita income levels, while C-T and M-SW zones had lower per capita incomes. Importantly, even between 1991–2018, the maximum per capita income for C-T and M-SW was only about 10,000 RMB per year (approximately 2,386 US dollars).

Table A.2: Descriptive statistics of variables used in the two-way fixed effects model

Zone	**obs**	**Dependent Variable: Share of Clean Energy (%)**				**Independent Variable: Per Capita Income (1,000 RMB)**			
		Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max
EC-NE	54	10.742	5.632	1.770	25.345	3.992	3.834	0.728	14.656
EC-NW	86	7.756	6.383	0.658	35.569	3.001	3.236	0.428	13.803
C-N	107	16.596	13.809	1.641	81.305	4.933	5.141	0.479	26.490
C-T	14	7.304	5.222	0.114	19.567	3.163	3.024	0.855	10.393
CW-YP	151	21.685	23.240	1.045	95.834	4.958	5.602	0.374	30.375
WW-S	69	22.378	21.116	0.919	84.333	4.409	4.166	0.541	17.821
M-SW	36	9.130	10.833	0.749	43.336	2.486	2.797	0.359	10.768

A.3 Detailed regression results of two-way fixed effects model

Table A.3 presents the detailed regression results shown in Figure 2.4.

Table A.3: Detailed regression results of two-way fixed effects model. The greater R^2 of C-T and M-SW may reflect the small samples in these two domestic energy use zones. All regressions control for the year and province fixed effects. Standard errors in parentheses are robustness standard errors obtained from R "clubSandwich" package developed by James E. Pustejovsky (Long & Ervin, 2000). These estimates use an unbalanced province-year level panel.

	Dependent Variable: Share of Clean Energy (%)						
	EC-NE	EC-NW	C-N	C-T	CW-YP	WW-S	M-SW
Per Capita Income	-1.333	0.304	0.599	0.767	1.897	5.232	10.556
	(0.390)	(0.682)	(0.897)	(0.448)	(0.318)	(1.022)	(0.074)
Observations	54	86	101	14	150	69	36
R-Squared	0.003	0.002	0.018	0.742	0.152	0.097	0.769
Province Fixed-Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes

A.4 Parameters of ARIMA(p, d, q) models

To determine the parameters of ARIMA models, we utilized the auto.arima() function in R. This function employs a variant of the Hyndman-Khandakar algorithm, which combines unit root tests, maximum likelihood estimation, and minimization of the corrected Akaike's Information Criterion (AICc) to obtain an "optimal" ARIMA model (Hyndman & Khandakar, 2008). In section "8.7: Arima modelling in R," Hyndman et al. (2018) provide a detailed explanation of the auto.arima() function.

The algorithm proceeds in the following manner: first, it determines the $d(0 \leq d \leq 2)$ in the model using repeated Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests for testing a null hypothesis that an observable time series is stationary around a deterministic trend against the alternative of a unit root (Kwiatkowski et al., 1992). Next, it selects the values of p and q by minimizing the AICc after differencing the data d times (e.g., in an ARIMA$(p, 1, q)$ model when $d = 1$, $y'_t = y_t - y_{t-1}$; in an ARIMA$(p, 2, q)$ model where $d = 2$, $y'_t = (y_t - y_{t-1}) - (y_{t-1} - y_{t-2})$. The algorithm starts with four initial models (i.e., ARIMA$(0, d, 0)$, ARIMA$(2, d, 2)$, ARIMA$(1, d, 0)$, and ARIMA$(0, d, 1)$), and uses a stepwise search to traverse the model space. The "best" model with the minimum AICc value among these four is set as the current model. The algorithm then varies the current model by incrementing or decrementing the p and/or q of the current model by 1 and including or excluding the constant from the current model. The best model considered thus far is selected as the new current model. This process is repeated until no further decrease in AICc can be obtained.

The program uses some approximations to speed up the search process, which may result in missing the minimum AICc. In order to enlarge the set of models, we use the approximation=FALSE and stepwise=FALSE options within the auto.arima() function. To avoid any missing of the "optimal" model, we also run several manual searches using arima() function as a double-check. Table A.4 and Table A.5 present the detailed parameters of the ARIMA models described in the main text, respectively.

Table A.4: Parameters and outcomes of the ARIMA(p, d, q) model in Figure 2.5. In the C-N region we only use the observations before the *Clean Heating Policy* to predict the business-as-usual rural household energy transition.

Area	Obs	ARIMA(p, d, q)	Coefficients	Sigma2	log likelihood	AICc	BIC	drift
EC-NE	28	ARIMA(2,1,0)	ar1: -0.110(0.17); ar2: -0.429(0.17)	2.335	-48.93	104.9	107.74	No
EC-NW	28	ARIMA(0,1,0)	drift: 0.561(0.28)	2.211	-48.51	101.52	103.62	Yes
C-N	24	ARIMA(0,1,0)	drift: 0.933(0.28)	1.874	-39.34	83.29	84.96	Yes
C-T	28	ARIMA(1,0,0)	ar1: 0.856(0.09); mean: 11.745(3.44)	10.05	-71.65	150.31	153.3	No
CW-YP	28	ARIMA(0,1,0)	drift: 2.136(0.72)	14.68	-74.07	152.63	154.73	Yes
WW-S	28	ARIMA(1,1,0)	ar1: -0.537(0.16); drift: 2.082(0.55)	20.27	-78.06	163.17	166.02	No
M-SW	28	ARIMA(0,1,0)	drift: 1.321(0.70)	13.69	-73.13	150.76	152.85	Yes

Table A.5: Parameters and outcomes of ARIMA(p, d, q) model in Figure 2.6.

Province	Obs	ARIMA(p, d, q)	Coefficients	Sigma2	log likelihood	AICc	BIC	drift
Beijing	24	ARIMA(0,1,0)	drift: 1.356(0.71)	12.1	-60.8	126.19	127.86	Yes
Tianjin	24	ARIMA(0,1,0)	/	18.95	-66.47	135.12	136.07	No
Hebei	24	ARIMA(0,1,1)	ma1: 0.689(0.14); drift: 1.017(0.33)	0.99	-31.79	70.84	72.98	Yes

Shanxi	24	ARIMA(2,0,0)	ar1: 0.637(0.18);
			ar2: 0.470(0.18);
			mean: 6.783(0.53)
				5.02	-52.17	114.44	117.05	No

Henan	24	ARIMA(0,1,0)	drift: 0.784(0.28)	1.83	-39.1	82.8	84.47	Yes

Shandong	24	ARIMA(4,1,2)	ar1: 0.019(0.31);
			ar2: 0.548(0.27);
			ar3: 0.115(0.19);
			ar4: 0.355(0.19);
			ma1: -0.16(0.29);
			ma2: -0.81(0.28)
				28.67	-68.69	158.85	159.33	No

A.5 Proportion of rural households with primary domestic energy in 2016

To maintain consistency between the first and third rounds of the China Agricultural Census data, we opted not to include the number of rural households using electricity as their primary domestic energy source in Figure 2.3(b). Figure A.1 displays the map illustrating the complete third-round census data on the "proportion of rural households with primary domestic energy sources," encompassing electricity as well.

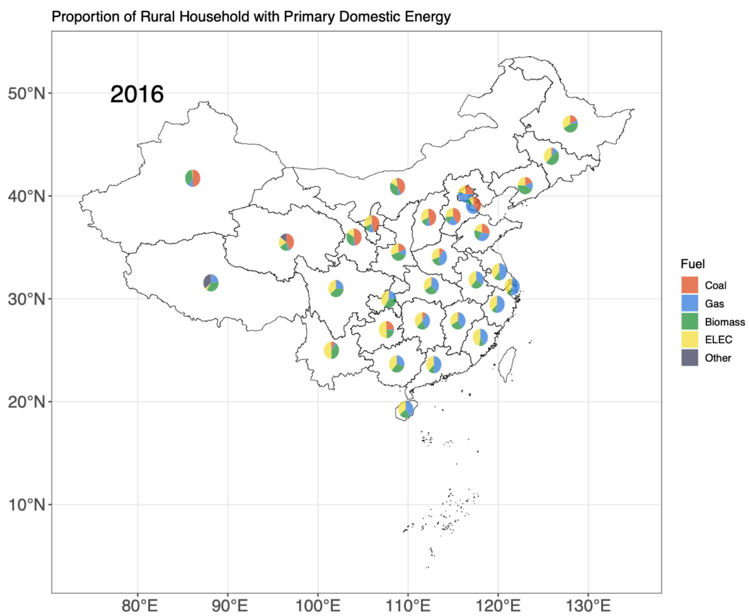

Figure A.1: Proportion of rural households with primary domestic energy in 2016.

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Appendix B

Appendix to Chapter 3

B.1 Sample: revisited households across waves

Figure B.1 illustrates the seasonal composition of the sample households, detailing the number of baseline households, those successfully revisited in each follow-up round, households with unsuccessful revisits, and newly recruited sample households.

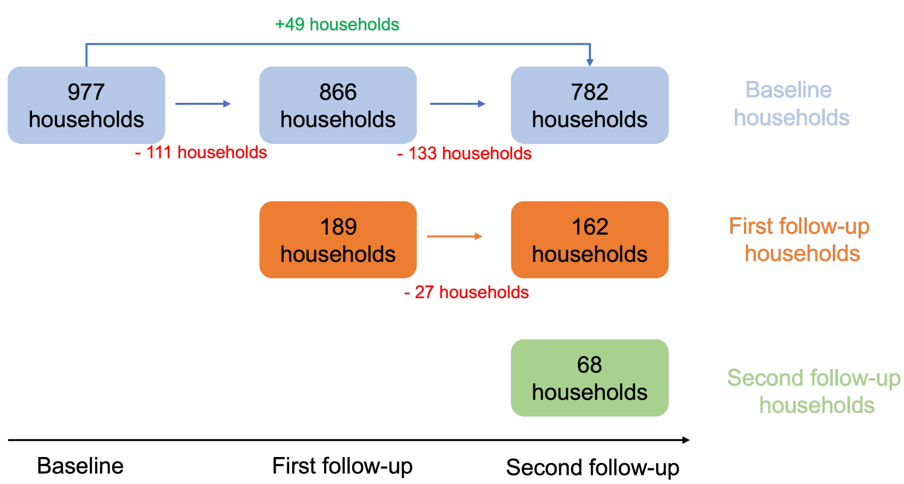


Figure B.1: Sample households of each wave.

B.2 Two-sample means t-test of key variables

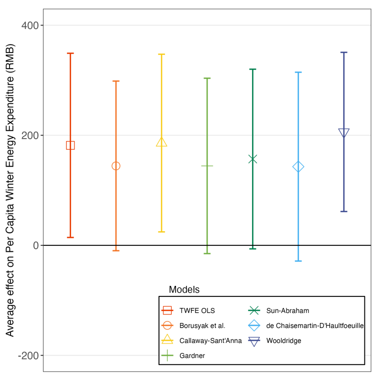
Although the DiD strategy does not require the treatment and control groups to have similar pre-treatment outcomes, we assess balance in pre-treatment key variables between never-treated and treated households using two-sample mean t-tests in the descriptive statistics. Table B.1 presents the results.

Table B.1: Two-sample means t-test of key variables. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

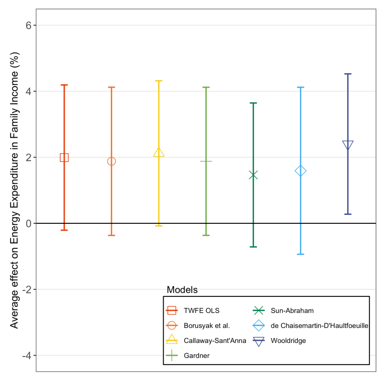
Variable	Never Treated			Treated Before			Diff		
	Obs	Mean	SD	Obs	Mean	SD	Obs	Diff	Std. Error
Economic Outcomes									
Per Capita Winter Energy Expenditure (Exp: RMB/person)	1512	1340	910	578	1170	764	2090	170***	42.6
Share in Family Income (Share: %)	1512	11.0	11.9	578	10.8	11.7	2090	0.218	0.577
Space Heating Outcomes									
Nighttime Indoor Temperature (Temp: °C)	730	14.0	3.72	228	13.1	4.13	958	0.824***	0.290
Rooms with Regular Heating (Rooms)	1505	4.48	2.62	577	3.96	2.45	2082	0.524***	0.126
Average Heating Duration (Duration: hours $\cdot$ day^{-1} $\cdot$ room^{-1})	1505	11.0	5.88	577	9.25	5.71	2082	1.72***	0.286
Controls									
Building age (years)	1512	16.5	14.9	578	14.6	13.1	2090	1.85***	0.706
Building area (m^2)	1512	118.8	50.8	578	134.7	53.4	2090	-15.9***	2.52
Number of Villages		30			20				
Number of Households		695			485				

B.3 Average treatment effects from different DiD estimators

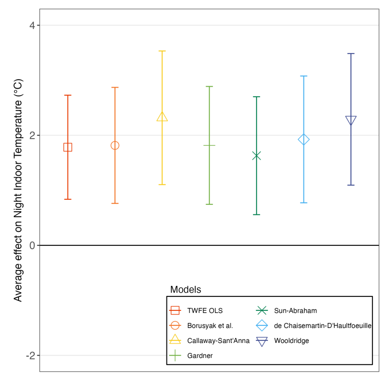
Figure B.2 illustrates the average treatment effects of the *Clean Heating Policy* on economic and physical measures of energy poverty, as estimated using a series of difference-in-differences (DiD) estimators. The results across these various estimators demonstrate a high degree of consistency.



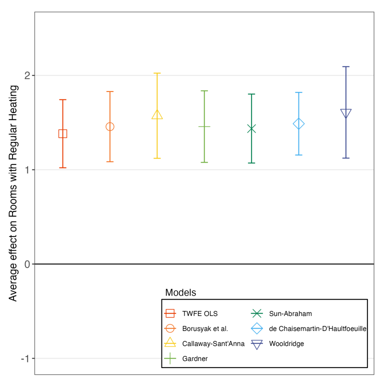
(a) Energy expenditure



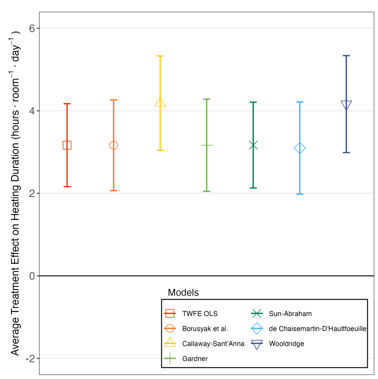
(b) Share in Income



(c) Nighttime temperature



(d) Heating rooms



(e) Average heating duration

Figure B.2: Average treatment effects from various DiD estimators.

B.4 Electricity tariff subsidies: "triple subsidies"

Figure B.3 illustrates the nighttime electricity tariffs for households participating in the *Clean Heating Policy* under the government's triple subsidies, alongside several scenarios discussed in Section 3.5.1.

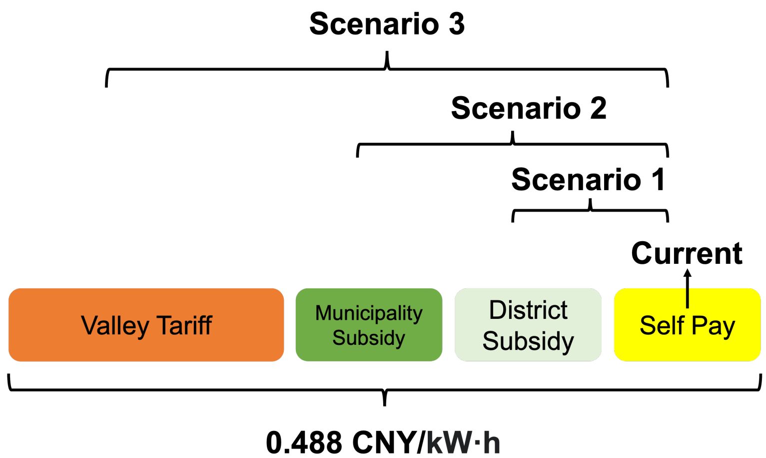
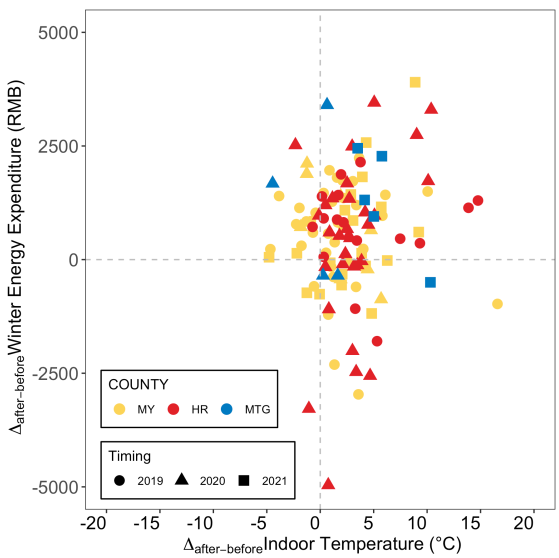
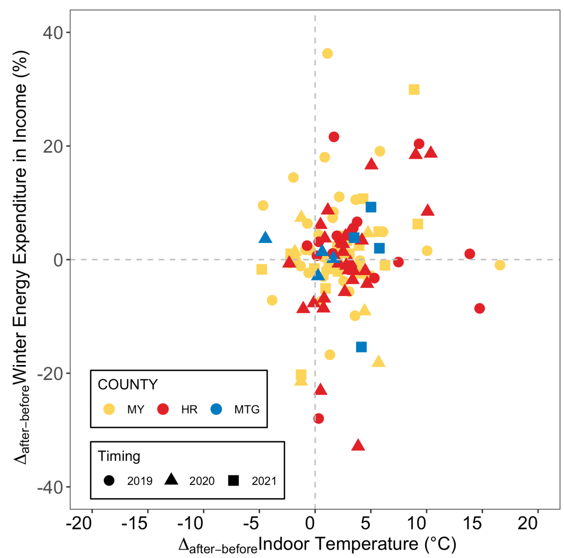


Figure B.3: Electricity subsidy scenarios.

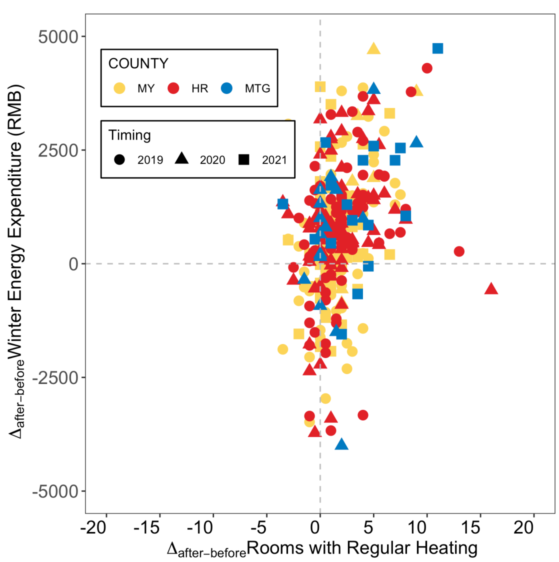
B.5 Trade-off between energy expenditure and space heating



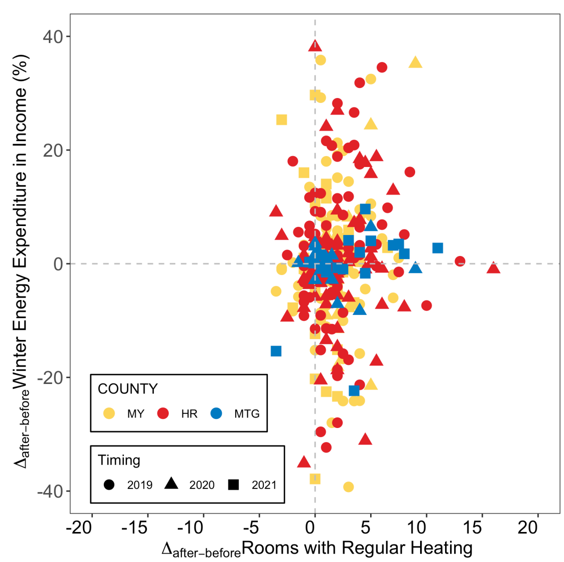
(a) Expenditure versus temperature



(b) Share versus temperature



(c) Expenditure versus heating



(d) Share versus heating

Figure B.4: Before-and-after difference in household economic and space hating outcomes for treated households.

B.6 Household wealth index: construction and validation

Figure B.5 illustrates the correlation between the baseline wealth index, used to categorize sample households into wealth groups as described in Section 3.4.4, and a series of socioeconomic variables, including assets and expenditures. The strong positive correlations demonstrate that the wealth index, calculated using principal component analysis (PCA), effectively profiles the households' wealth status.

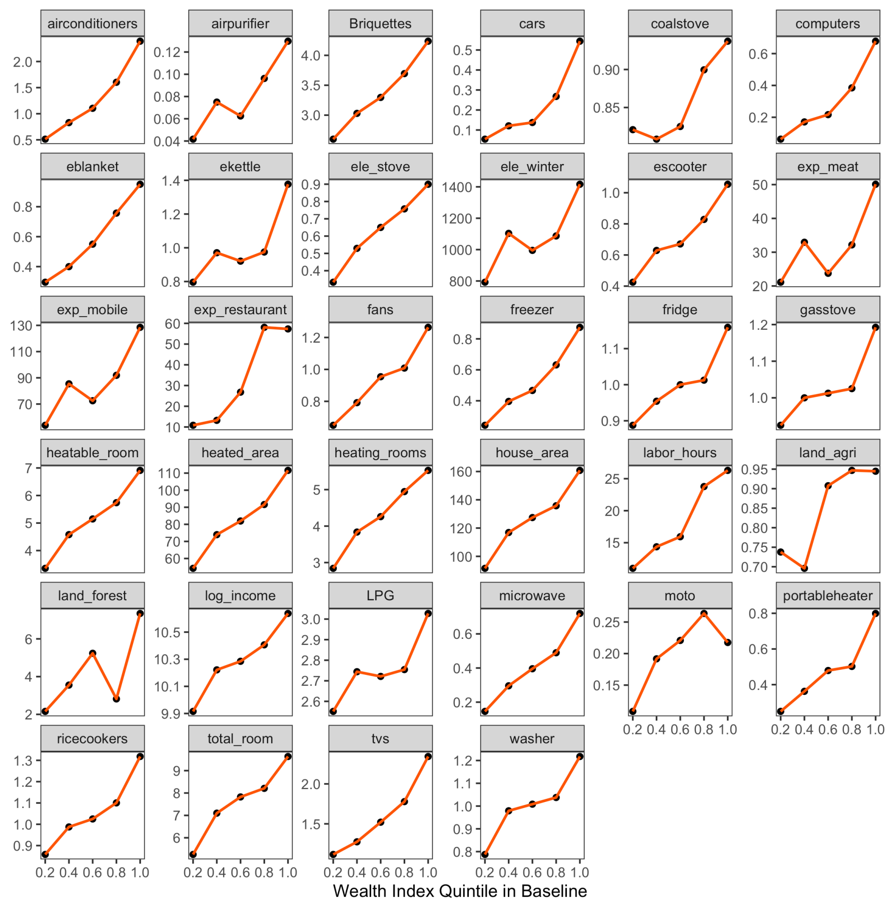


Figure B.5: Correlation of wealth index group with socioeconomic indicators.

B.7 Popularity of hot water radiators across wealth groups

Figure B.6 shows a positive correlation between the share of households equipped with water radiator systems and wealth index groups at baseline. Specifically, a higher proportion of households in the more affluent wealth index groups had water radiator systems installed at baseline.

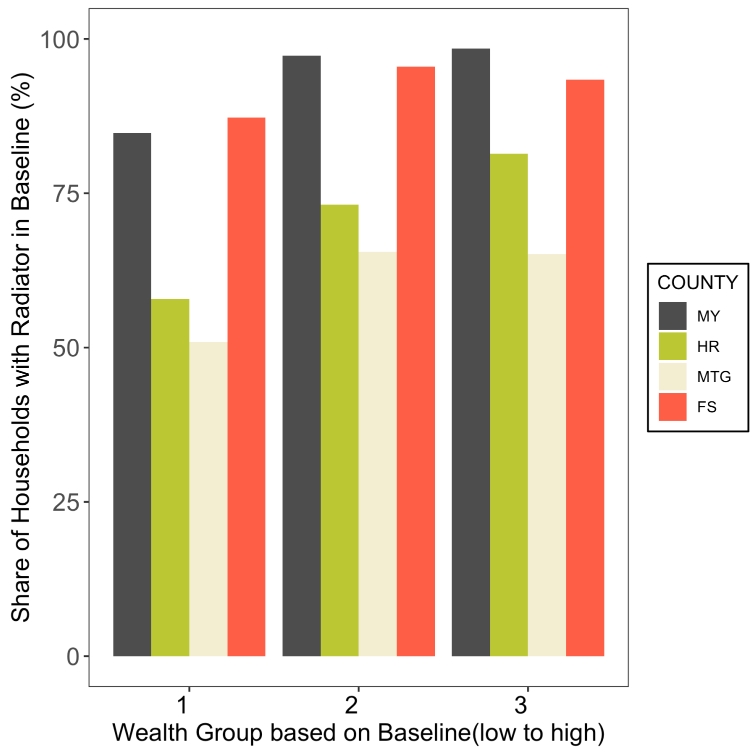


Figure B.6: Share of households equipped with water radiator systems at baseline across various districts and wealth groups.

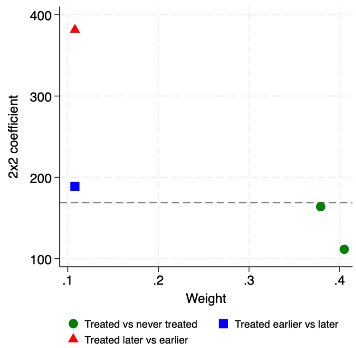
B.8 Descriptive statistics of outcomes: treated versus uptake

Table B.2 compares the outcomes of interests in **Chapter 3** between the treated by the *Clean Heating Policy* and actually uptake the new heating practice from the *Clean Heating Policy*. The results indicated that the uptake group exhibited slightly higher outcomes than the treated group, although the difference was slight.

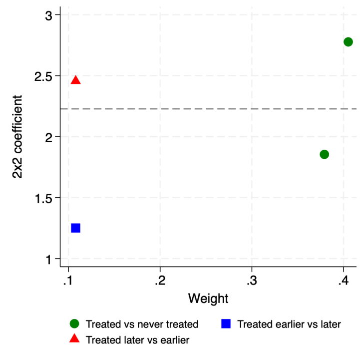
Table B.2: Descriptive statistics of outcomes after treatment.

	Treated			Uptake		
	Obs	Mean	SD	Obs	Mean	SD
Economic outcomes						
Per capita winter energy expenditure						
(Exp: RMB/person)	597	1586.37	938.62	571	1617.96	942.77
Share in family income (Share: %)	597	11.94	13.04	571	12.14	13.21
Space heating outcomes						
Nighttime indoor temperature (Temp: °C)	284	15.86	3.46	275	15.93	3.39
Rooms with regular heating (Rooms)	595	5.93	3.12	570	6.04	3.11
Average heating duration						
(Duration: hours $\cdot$ day^{-1} $\cdot$ room^{-1})	595	12.62	4.87	570	12.86	4.76

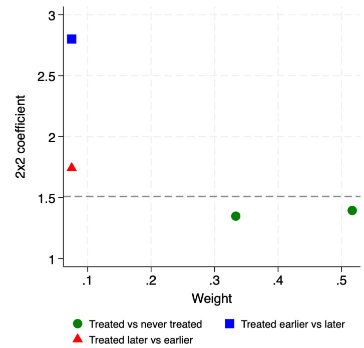
B.9 Bacon decomposition



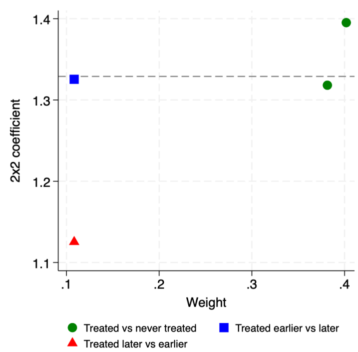
(a) Energy Expenditure



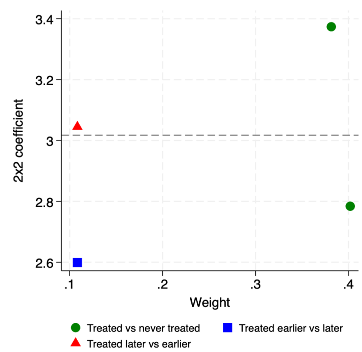
(b) Share in income



(c) Nighttime temperature



(d) Heating rooms



(e) Average heating duration

Figure B.7: Bacon decomposition of TWFE DiD estimator. This figure shows the bacon decomposition results of all the 2×2 TWFE estimations of the economic and space heating impacts as well as their weights. The treated versus never treated is shown as green circles. The red triangle represent late versus early treated combinations. The blue square represents the early versus late treatment groups. The horizontal dashed line represents the TWFE estimation of the average treatment effect, which is the weighted average of all 2×2 estimator. Due to the bacon decomposition is performed with strongly balanced panel data, the average treatment effects are slightly different from our main regression results. To obtain a more robust results, the controls were not include in this analysis.

B.10 Before-and-after distribution of energy expenditure among treated households

Figure B.8 presents concentration curves depicting the cumulative distribution of winter energy expenditures for households in the treatment group, sorted by wealth index, before and after the *Clean Heating Policy*. Households with a lower wealth index experienced an increased share of energy expenditure in their total household costs after the implementation of the *Clean Heating Policy*. Consequently, these households now bear a greater financial burden than before.

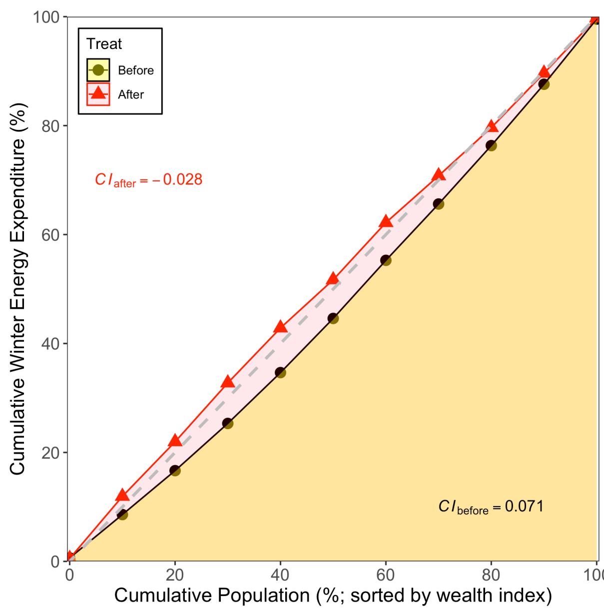


Figure B.8: Before-and-after distribution of energy expenditure among treated households: concentration curve.

Appendix C

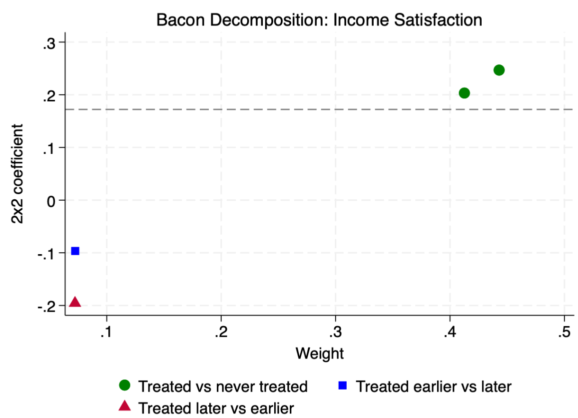
Appendix to Chapter 4

C.1 Bacon decomposition

The TWFE estimator in staggered difference-in-differences settings is a weighted average of various 2×2 DiD comparisons (Goodman-Bacon, 2021). Our analysis reveals that the TWFE estimator effectively captures average treatment effects compared to heterogeneity-robust estimators. Bacon decomposition (Figure C.1) demonstrates that comparisons between "Treated and never-treated groups" (green circles) contribute over 80% to the TWFE estimate, while the "bad" comparisons between "Treated later vs earlier" (red triangles) account for only 7%. This suggests that the influence of potential biases related to taking earlier treated as control is relatively limited in our analysis.

(a) Life satisfaction

(b) Satisfaction with living conditions



(c) Satisfaction with income

Figure C.1: Bacon decomposition of subjective well-being impacts with TWFE estimator. This figure shows the bacon decomposition results of all the 2×2 TWFE estimations of the subjective well-being impacts as well as their weights. The treated versus never treated is shown as green circles. The red triangle represent late versus early treated combinations. The blue square represents the timing groups or early versus late treatment groups. The horizontal dashed line represents the TWFE estimation of the average treatment effect, which is the weighted average of all 2×2 estimator. Due to the bacon decomposition is performed with strongly balanced panel data, the average treatment effects are slightly different from our main regression results. To obtain a more robust results, the controls were not include in this analysis.

C.2 Average treatment effects with interactive fixed effects

To address potential endogeneity arising from time-varying unobserved factors, we incorporate an interactive household-year fixed effects, $\zeta_i' F_t$, following Bai (2009), as shown in Equation C.1.

$$Y_{it} = \mu_i + \lambda_t + \zeta_i' F_t + \beta \times \text{Treat}_{it} + X_{it} \times \gamma + \epsilon_{it} \tag{C.1}$$

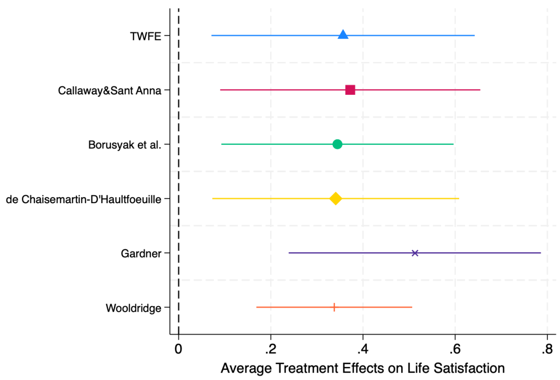
Here, ζ_i' represents a vector of factor loadings, while F_t is a vector of common factors. The interactive term $\zeta_i' F_t$ accounts for the impacts of unobserved, time-invariant factors that change over time. Table C.1 presents results of different specifications with and without this interactive fixed effect term. While life satisfaction and satisfaction with living conditions estimates remain consistent, satisfaction with income effect shifts from positive to negative but remains small and statistically insignificant.

Table C.1: Robustness check with interactive of fixed effects. Each column presents estimates from a separate regression using the same dataset but varying fixed effects. Columns (1), (3), and (5) replicate corresponding estimates in Table 4.2 in main text. Standard errors in parentheses are clustered at the village level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

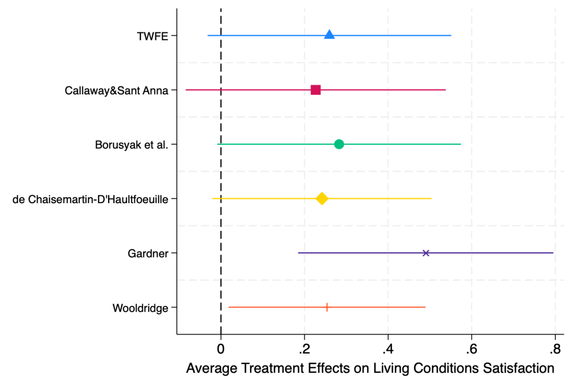
	Life Satisfaction		Satisfaction with Living Conditions		Satisfaction with Income	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.36**	0.36	0.26*	0.20	0.10	-0.17
	(0.14)	(0.25)	(0.14)	(0.25)	(0.20)	(0.38)
Observations	2,789	2,789	2,789	2,789	2,789	2,789
Mean Dep.Var.	7.70	7.70	7.50	7.50	5.55	5.55
Household FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Household×Year FE		✓		✓		✓
Controls	✓	✓	✓	✓	✓	✓

C.3 Average treatment effects of heterogeneity-robust estimators

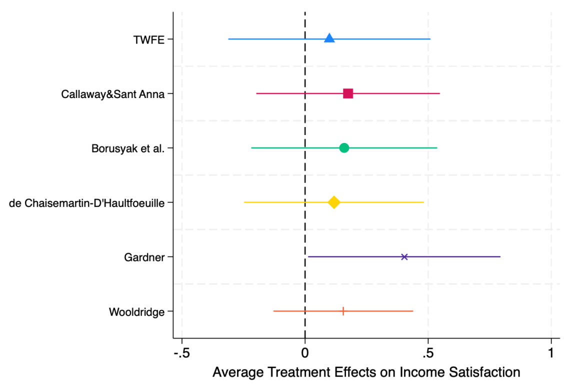
To address concerns about the TWFE estimator in staggered DiD settings, we present event study results using various heterogeneity-robust DiD estimators in main text. Figure C.2 illustrates the average treatment effects on life satisfaction, satisfaction with living conditions, and satisfaction with income across these estimators, including TWFE, Gardner (2022), Callaway and Sant'Anna (2021), Wooldridge (2021), De Chaisemartin and d'Haultfoeuille (2020), Borusyak et al. (2021) . Except for the slightly larger point estimates from Gardner (2022), the average treatment effects across estimators are remarkably consistent in magnitude and statistical significance. This suggests our baseline TWFE regression is robust even in this staggered DiD context.



(a) Life satisfaction



(b) Satisfaction with living conditions

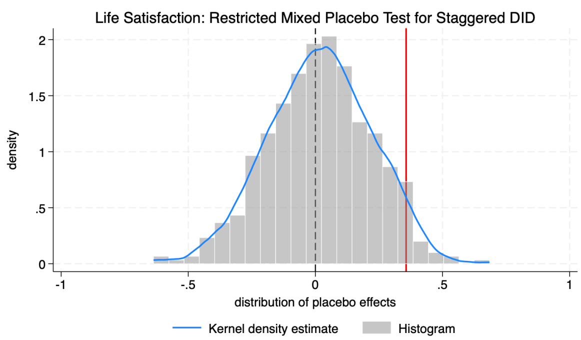


(c) Satisfaction with income

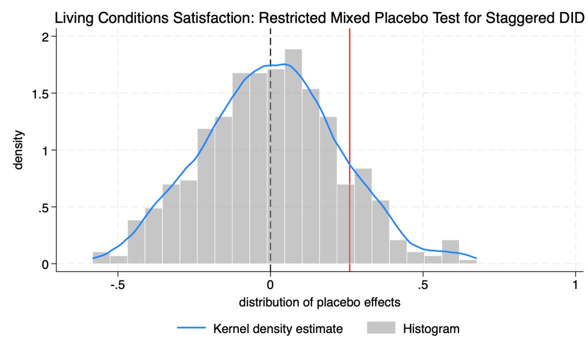
Figure C.2: Average treatment effects on subjective well-being with heterogeneity-robust DiD estimator. This figure shows the average treatment effects on subjective well-being constructed using six different estimators: the TWFE model, Equation 4.1, estimated using OLS (in blue with triangle markers); Callaway and Sant'Anna (2021) (in red with square markers); Borusyak et al. (2021) (in green with circle markers); De Chaisemartin and d'Haultfoeuille (2020)(in yellow with diamond markers);Gardner (2022) (in purple with cross markers); and Wooldridge (2021) (in orange with line markers). The intervals are the 95 percent confidence intervals based on standard errors clustered at the village level.

C.4 Restricted mix DiD placebo test

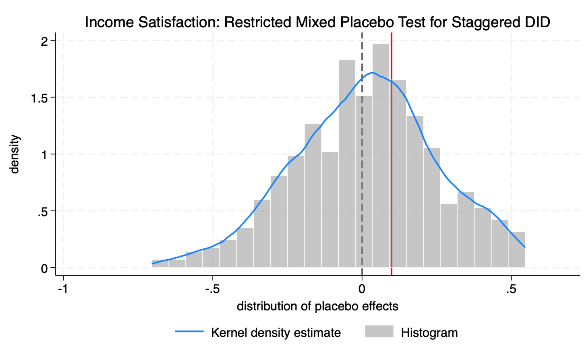
In addition to the in-space and in-time placebo tests presented in the main text, we conducted a restricted mixed DiD placebo test using the "didplacebo" Stata package (Chen et al., 2023). This test incorporates both "fake treatment units" and "fake treatment timing" while preserving the original cohort structure (i.e., number of treated units in each cohort). Notably, in the distribution of placebo estimates as shown in Figure C.3, only 6% exhibited a greater absolute value than our main estimate of the average life satisfaction impact.



(a) Life satisfaction



(b) Satisfaction with living conditions



(c) Satisfaction with income

Figure C.3: Restricted mixed placebo test of subjective well-being impacts. The gray bars and blue lines illustrate the distribution of 500-time Monte Carlo analysis on estimation of Equation 4.1 but "fake" treatment status. The solid black vertical lines represent the main estimation results based on the treatment status in reality. The dashed lines represent the impacts of zero.

C.5 Life satisfaction distribution of untreated households

To address concerns about potential response bias in life satisfaction reporting, we present the distribution of life satisfaction scores among untreated households across survey years (Figure C.4). The responses exhibit a left-skewed distribution, with most participants selecting the top value (ten out of ten) each year. This is particularly pronounced in the final survey year, where over 40% of participants chose the top value. Additionally, 8 out of 10 emerges as the second most popular choice, likely due to its cultural significance as a fortunate number in China. The middle values of five or six are also common, potentially attributable to the "focal response" phenomenon often discussed in the literature. Six, similar to eight, also holds positive connotations in Chinese culture. As another case of common focal response, the low value of 0 is less common in our sample.

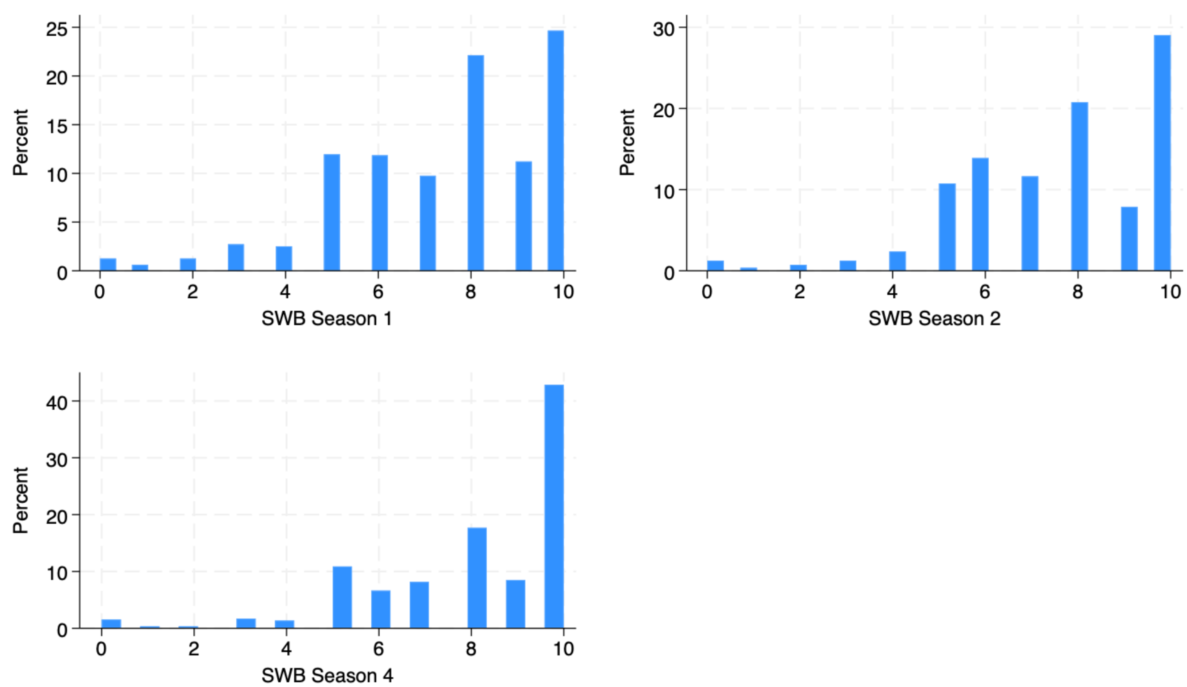


Figure C.4: Life satisfaction distribution of untreated households across waves.

C.6 Robustness check of the "focal" response on life satisfaction

To assess the potential impact of "focal point" responses (selecting the top value) on the robustness of our life satisfaction estimates, we replicated the baseline regression and in-time placebo test using a subsample excluding all observations with the top life satisfaction response (10). Figure C.5 presents these results. While the main estimate remains consistent with the full sample, excluding focal responses weakens the statistical significance of the in-time placebo test.

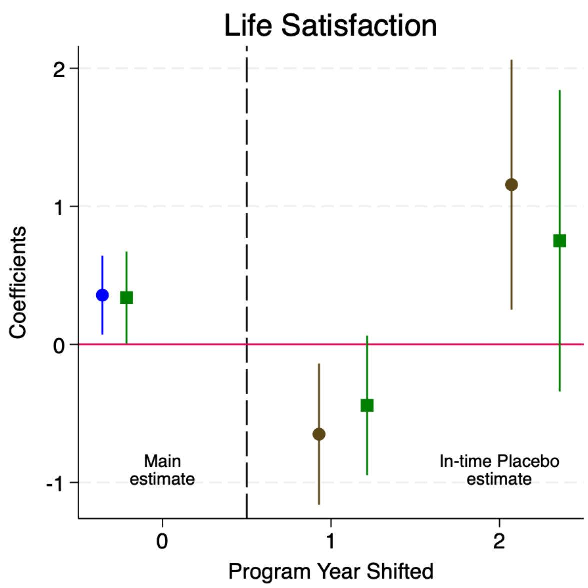


Figure C.5: Robustness check of the "focal" response on life satisfaction.

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