To Go Electric or To Burn Coal? A Randomized Field Experiment of Informational Nudges*

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Abstract

Coal heating in residential homes is an important source of indoor air pollution, leading to detrimental health effects. We conduct a randomized field experiment in northern China using three types of SMS campaigns targeting three potential biases that may hinder the adoption of electric heating: a Cost SMS campaign, designed to address the overestimation of electricity expenses; a Health SMS campaign, aimed at addressing the underestimation of health damage associated with coal heating; and a Social Comparison SMS campaign, intended to inform households about the popularity of electric heating. We find that the Cost SMS backfires: it instead leads to a substantial reduction in electric heating, which can be attributed to salience bias induced by the Cost SMS, which drew heightened attention to the cost of electricity. The Health SMS is ineffective for households that underestimate the health damage of coal heating and even backfires for those who expressed little concern about the health consequences. Social Comparison SMS is only effective for a small proportion of households who were concerned about their neighbours' heating choices. Overall, our findings suggest that SMS campaigns targeting these biases are largely ineffective, and caution should be exercised when applying plausible nudge interventions. The findings also suggest that households may be motivated to maintain their beliefs and resist paternalistic interventions.

Keywords: Electric Heating; Nudge Interventions; Environment; Field Experiment
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1 Introduction

According to the World Health Organization (WHO), 3.8 million lives, representing 7.7% of global mortality, were lost in 2016 due to indoor air pollution (Huang et al., 2018).[1] The utilization of inefficient and carbon-intensive biomass, such as coal, fuel-wood, and straw energy, for heating purposes poses a significant indoor air pollution challenge, especially for individuals residing in rural areas of developing nations. Medical studies indicate that exposure to indoor pollution resulting from coal heating is closely linked to higher rates of mortality and morbidity. (Mumford et al., 1987; Ando et al., 1998; Finkelman et al., 1999; Zhang and Smith, 2007; Pérez-Padilla et al., 2010; Barreca et al., 2014). Undoubtedly, coal burning stands out as a prominent contributor to greenhouse gas emissions. Consequently, the promotion of clean heating has become increasingly crucial for developing countries, as it plays a significant role in reducing air pollution, enhancing public health, and addressing the challenges posed by climate change.

Despite the evident environmental and health benefits, the voluntary adoption of cleaner electric heating in developing countries has been sluggish. A notable example is China, where over one-third of households continue to rely on coal burning stoves for their heating needs (Duan et al., 2014; Barrington-Leigh et al., 2019). In 2016, coal heating in households constituted 31.6% of the overall heating in northern China, resulting in an annual coal consumption of approximately 200 million tons, as reported by China's Clean Winter Heating policy (2017–2021).[2] Understanding the reasons behind households' reluctance to transition to cleaner heating methods holds significant policy implications.

This paper presents the findings from a randomized field experiment of informational nudges conducted in a northern Chinese province. The objective was to investigate the barriers that impede households from adopting cleaner electric heating and to assess the effectiveness of simple SMS nudges in promoting the switch to electric heating. The experimental design specifically targeted three potential biases that may contribute to households' resistance towards electric heating: (1) the overestimation of electricity costs; (2) the underestimation of health damages associated with coal heating; and (3) households' motivations driven by social comparisons.

Our study is divided into two stages. In the first stage, we conducted a pre-treatment survey to gather data on households' heating preferences and other relevant characteristics. This survey enabled us to identify diverse motivations behind households' resistance to electric heating and evaluate the heterogeneous effects of information nudges for households with different baseline characteristics. In the second stage, households were randomly assigned to one of three types of SMS campaigns: Cost SMS, Health SMS, and Social Comparison SMS. Each campaign targeted a specific potential bias associated with the adoption of electric heating, namely, the overestimation of costs, the underestimation of health damages, and social comparison influences, respectively.

To be more specific, the Cost SMS campaign delivers accurate information regarding households' daily electricity expenses. The Health SMS campaign provides information on the potential health damages associated with coal heating. Lastly, the Social Comparison SMS campaign

[1] Data on mortality from household air pollution is available at `https://www.who.int/gho/phe/indoor_air_pollution/burden/en/`.

[2] See China's Winter Heating policy (2017–2021) in Chinese.

shares information about the percentage of households in nearby villages that have successfully transitioned to electric heating. These SMS interventions span an 8-day period in February 2019. We collected daily electricity consumption data from the local electricity company for a ten-week period, starting from four weeks prior to the SMS intervention and continuing for six weeks after. Additionally, we gathered daily electricity consumption data from October 2019 to March 2020 to estimate the long-term effects of the interventions. To assess the impact of the SMS campaigns, we employed a standard difference-in-differences (DID) framework, comparing changes in electricity consumption between the treatment groups and the control group.

A notable aspect of our study is the inclusion of information regarding subjects' biases and motivations that could influence their choices between coal and electric heating. This information is collected through a pre-experiment survey, which sets our study apart from much of the existing literature that overlooks individual heterogeneity beliefs. To be more specific, we assess subjects' potential overestimation of electricity expenses by comparing their estimates of their electricity bill for the day before the survey (January 24, 2019) with their actual expenses.[3] Additionally, we elicit subjects' beliefs on the impact of coal heating on life expectancy to measure their potential underestimation of health damages caused by coal heating. Furthermore, we measure subjects' social comparison bias by inquiring about the importance of neighbors' decisions when making heating-related choices. Moreover, we elicit subjects' time preferences to investigate whether the preference for coal heating could be influenced by present biases. These measurements enable us to conduct a thorough analysis of heterogeneity regarding the effectiveness of the SMS nudges.

Paternalistic Intervention. The three biases mentioned earlier can also be understood as forms of imperfect information. The SMS interventions play a crucial role in reducing this imperfect information, thereby assisting households in making better choices and improving overall welfare and efficiency. Imperfect information is often cited as a justification for paternalistic interventions (Allcott, 2016; Glaeser, 2005) or as a basis for libertarian paternalism (Thaler and Sunstein, 2003) that aim to guide choices without restricting them. Our SMS campaigns can be seen as such paternalistic nudges. However, it is possible that households perceive these interventions as paternalistic and respond by making choices that contradict the intended objective of the intervention, such as opting for reduced electric heating. Understanding whether individuals exhibit aversion towards paternalistic interventions is crucial for designing effective behavioral public policies. To the best of our knowledge, our study is the first to document that individuals may demonstrate hostility towards paternalistic nudges, particularly in the context of environmental issues (see Croson and Treich, 2014 and Allcott and Mullainathan, 2010 for a review).[4]

Overestimation of Electricity Expenses. Compared to coal heating, electric heating incurs higher costs in terms of both upfront equipment expenses and ongoing energy expenditure. For instance, in Mongolia, the monthly heating bill for electricity can be twice as much as

[3]The elicitation is incentivized in the sense that they would receive RMB 5 ($\approx$ US$ 0.76 at then-prevailing exchange rate) if their estimates were within a range of the actual electricity expense.

[4]Thaler and Sunstein (2003) offer evidence highlighting the positive aspects of nudges within the framework of libertarian paternalism.

that for coal heating (World Bank, 2009). Villagers often come across reports and discussions regarding the elevated cost of electric heating through various channels such as newspaper articles, television reports, online sources, and word-of-mouth rumors.[5] During the pre-experiment survey, we gathered data on the participants' estimated electricity expenses for the day prior to the interview, which revealed that a significant majority (85%) of the respondents overestimated their electricity expenses. For these participants, we hypothesized that the Cost SMS, designed to mitigate the overestimation bias, could potentially increase the adoption of electric heating if concerns about the high cost of electricity were the primary barrier to its adoption. However, the Cost SMS might also make the electricity cost a more salient decision factor, potentially hindering the adoption of electric heating instead.

Underestimation of the Health Damages of Coal Heating. The Health SMS aims to tackle the participants' lack of awareness regarding the potential health damages associated with coal heating. This lack of awareness is likely attributed to the fact that the detrimental health consequences of coal heating become evident only in the long term. Our pre-experiment survey revealed that 75% of the participants underestimated the health damages caused by coal heating. By enhancing participants' understanding of the adverse health effects linked to coal heating, we hypothesize that the Health SMS can encourage a greater adoption of electric heating. However, it is also plausible that the Health SMS may induce an opposite response due to the negative emotions triggered by the mention of various diseases associated with indoor air pollution.

Social Comparisons. If villagers have a preference to conform to their neighbors' choices, they are more likely to opt for coal heating if they underestimate the prevalence of electric heating in the community. The Social Comparison SMS aims to provide villagers with updated information about the popularity of electric heating, potentially leading to a shift in their heating choices. Notably, studies have demonstrated that social comparison can influence energy consumption (Allcott and Rogers, 2014) as well as choices in various other domains, such as driving (Chen et al., 2013) and voting (Gerber and Rogers, 2009).

Present Bias. Households might choose coal heating over electric heating due to present bias, both because coal heating is more affordable, and that the health damages associated with coal heating are often invisible and accumulate gradually over time. On the other hand, the primary benefit of electric heating, which is improved health, is unlikely to be immediately or directly observable. Consequently, we hypothesize that households with present bias are more inclined to choose coal heating. Indeed, a body of literature demonstrates that present bias is associated with sub-optimal behaviors, such as excessive credit card borrowing (Meier and Sprenger, 2010) or low uptake of welfare benefits (Fang and Silverman, 2009).

Targeting. Our experiment also aims to examine the significance of targeting in SMS nudge interventions. By eliciting a diverse range of biases and preferences, we are able to test the

[5]Related news reports are available at https://www.sohu.com/a/289023244_651697; http://finance.sina.com.cn/chanjing/cyxw/2017-03-28/doc-ifycstxp5282021.shtml; and http://www.china-heating.com/news/2017/34882.html.

hypothesis that SMS interventions need to be specifically tailored in order to be effective. Costa and Kahn (2013) discovered that individuals who identify as liberal/environmentalists are more likely to positively respond to energy conservation nudges compared to those with conservative political leanings. In contrast to their study, which focused on political ideology, our investigation centers around the "biases" exhibited by the households.

Our main findings can be summarized as follows. Providing feedback on electricity expenses resulted in a 52% *decrease* in the demand for electric heating. This effect was particularly pronounced among individuals who did not overestimate their electricity expenses, had concerns about costs, and faced financial constraints. Notably, the Cost SMS was not effective in encouraging households with cost overestimation to switch to electric heating. This finding is remarkable, considering the prevalent occurrence of overestimating electricity expenses within our sample population. It is consistent with the hypothesis that the Cost SMS brings the salience of electricity expenses to the forefront (Sims, 2003; Chetty et al., 2009; Finkelstein, 2009; Brown et al., 2010; Lacetera et al., 2012; Tiefenbeck et al., 2018), thereby motivating households to engage in cost savings. Additionally, this finding supports the hypothesis that households may hold "motivated beliefs" (Bénabou and Tirole, 2002; Compte and Postlewaite, 2004; Brunnermeier and Parker, 2005) that perceive electricity costs as high and exhibit aversion towards paternalistic interventions.

On average, the Health SMS campaign did not have a significant effect on the uptake of electric heating. However, it was effective for households that correctly perceived the health damage associated with coal heating and viewed health as important, resulting in a notable 55.8% and 25.6% increase in electric heating adoption, respectively. Conversely, the Health SMS had no significant impact on households that underestimated the health damage from coal heating. This outcome can potentially be explained by motivated beliefs, as these households might choose to maintain their biased belief to minimize anxiety stemming from the fear of negative health effects linked to coal heating. Furthermore, these households may have negative sentiments towards the Health SMS, perceiving it as a paternalistic intervention due to its mention of health damages, and responded to the negative sentiment by reducing their electric heating usage. Notably, individuals who indicated a lack of concern regarding health consequences experienced a 25.4% reduction in electric heating after receiving the Health SMS. In the case of the Social Comparison SMS campaign, its effectiveness was observed primarily among individuals who took their neighbors' heating choices into account. Lastly, we did not find a significant correlation between heating choices and the present bias.

Overall, our findings indicate that SMS interventions targeting imperfect information are largely ineffective, primarily due to salience bias or motivated beliefs held by households. The overall lack of effectiveness in SMS interventions suggests that households tend to resist paternalistic interventions, highlighting the necessity for a more targeted approach that focus on recipients who are potentially receptive to such interventions.

The remainder of the paper is structured as follows. In Section 2, we provide an overview of the related literature; in Section 3, we outline the experimental design; in Section 4, we present the summary statistics of our data; in Section 5, we describe the estimation strategy; in Section 6, we report the experimental results; finally, in Section 7, we conclude.

2 Related Literature

Extensive research on information nudges has demonstrated that providing information through methods such as social comparison, real-time feedback, commitment, and goal setting can effectively promote socially desirable behaviors. These information nudges have proven to be cost-effective in various domains, including energy conservation, the adoption of energy-efficient light bulbs, financial savings, selection of preventive health plans, and proper fertilizing practices (Allcott and Taubinsky, 2015; Thaler and Sunstein, 2009; Clark et al., 2014; Anderson and Robinson, 2018; Duflo et al., 2011). Despite extensive research on information nudges, the existing literature does not provide conclusive evidence regarding their effectiveness in driving desirable behavioral changes. For instance, Banerjee et al. (2021) demonstrate that SMS campaigns alone do not significantly improve immunization rates. However, there are instances where simple SMS reminders have proven effective in increasing savings rates among bank customers (Karlan et al., 2016) and increasing gym attendance members (Calzolari and Nardotto, 2017). These varying outcomes highlight the nuanced nature of information nudges and the need for further exploration to understand their effectiveness in different contexts.

Our information treatments revolve around the notion that overestimating electricity expenses, underestimating the potential health damages from coal heating, and lacking social comparison motivation can act as deterrents for households to adopt electric heating. In this section, we delve into the relevant literature pertaining to each of the treatments: the Cost SMS treatment, the Health SMS treatment, and the Social Comparison SMS treatment.

Cost SMS. Allcott and Taubinsky (2015) conducted an online experiment to demonstrate that providing consumers with information about the energy-saving qualities of compact fluorescent light bulbs (CFLs) effectively increased customers' willingness to pay (WTP) for CFLs. However, their field experiment yielded no significant effect on actual CFL purchases. Similarly, Beltramo et al. (2015) conducted a field experiment where they provided consumers with information on the private benefits of energy-saving cooking stoves, but found no significant effect on consumers' WTP for these appliances. The lack of conclusive results in these two studies may be attributed to the possibility that consumers already had misperceptions about the provided information prior to the intervention. To address this concern, we assessed households' perceptions of energy costs in a baseline survey by eliciting their estimated electricity expenses.

Furthermore, it is crucial to acknowledge that electric heating differs from CFLs and energy-saving cooking stoves in two significant ways. Firstly, the decision to switch to electric heating carries high stakes for our study population. Unlike CFLs and energy-saving stoves that generate cost savings, electric heating actually leads to an increase in energy costs ranging from 25% to 150% compared to the cost of coal heating in northern China (Zhou et al., 2020; Du et al., 2018).[6] Secondly, the long-term non-pecuniary health benefits associated with electric heating

[6]Similarly, in a companion study conducted in nearby villages where most households have already transitioned to electric heating, we found that the monthly cost of electric heating is approximately twice that of coal

are not immediately observable.

Other empirical studies have explored the impact of providing information about lifetime energy costs through labeling (Heinzle, 2012; Newell and Siikamäki, 2014; Davis and Metcalf, 2016; Deutsch, 2010a,b). These studies reveal that disclosing lifetime energy cost information can influence users to opt for more energy-efficient products. However, these findings are based on hypothetical choice experiments or assessments of online purchase intentions, rather than actual purchasing behavior.

Health SMS. Beltramo et al. (2015) also investigated the impact of informing consumers about the health benefits of energy-efficient cooking stoves on their willingness to pay (WTP), but found no significant effect of the information provided. The lack of a significant effect in their study may be attributable to a potential conflict of interest, as the information was communicated through a marketing message. Additionally, the health information provided was somewhat ambiguous and lacked specificity, with statements such as "This stove can improve health." In contrast, in our study, the information was conveyed by a research team from ShanghaiTech University, making it clear to the participants that no specific product was being promoted. Furthermore, the team provided comprehensive and detailed health information regarding the various diseases associated with coal heating.

Social Comparison SMS. Allcott and Rogers (2014) conducted a large-scale experiment involving over 6 million households in the United States to investigate the impact of social comparison on electricity conservation. They found that households receiving social comparison information reduced their electricity consumption by approximately 1% to 1.3% compared to the control group. Similarly, Chen et al. (2017) conducted a large-scale field experiment to study the influence of social comparison on driver behavior. They sent text messages to drivers regarding the driving habits of other drivers with similar or luxury cars. Chen et al. (2017) argued that combining social status with descriptive norms is effective in promoting better driving behavior. While these studies demonstrate the influence of social comparison on behavior, it remains unclear whether individuals would modify their behavior if only a few others engage in the desired behavior. In our study, this phenomenon is exemplified by the relatively low adoption of electric heating. Ulph and Ulph (2018) argue that individuals will only conform to a new norm if the number of others adopting that behavior surpasses a specific threshold. Our study provides empirical evidence regarding the conditions under which social comparison can effectively establish a new desired norm when the new norm is less popular and more expensive than the prevailing one.

3 Experimental Design and Interventions

3.1 Experimental Design

Our study took place in two villages located in Anyang, a city situated in the northernmost region of Henan Province, China. Similar to many other villages in northern China, the partic-

heating. Specifically, the average monthly cost of electric heating amounts to around RMB 243 (≈ US$38), while the average monthly expense for coal heating was approximately RMB 122 (≈ US$19).

ipants in our study predominantly used coal-burning stoves for winter heating. However, it is worth noting that 90% of the villagers possessed at least one electric heating device, such as a heater or an air-conditioner, in their homes.

Our experiment consisted of two stages. In the first stage, we invited households to participate in a baseline survey. The primary aim of this survey was to gather information about the villagers' heating preferences, explore the factors driving these preferences, and collect demographic characteristics. To assess heating preferences, we initially requested participants to state their preferred heating choice. To minimize the likelihood of socially desirable responses, we then engaged in detailed conversations where participants could elaborate on the reasons behind their preferences. Additionally, we sought to elicit participants' estimations of the ongoing cost of electric heating and the health damage associated with coal heating through incentivized questions. This allowed us to determine whether participants had any perception biases regarding these issues prior to the interventions. We also inquired about the relative importance of different factors influencing their heating choices. Specifically, we asked villagers to consider the importance of price, health impact, environmental impact, and the decisions of their neighbors when making their heating decisions. These questions align with the three obstacles we hypothesized as potential barriers to adopting electric heating.

During the survey, we also collected participants' time preferences using a set of incentive-compatible time preference questions used in previous studies (Harrison et al., 2002; McClure et al., 2004; Meier and Sprenger, 2010). These questions aim to provide insights into whether present bias plays a role in the participants' aversion to electric heating, particularly because electric heating is more expensive than coal heating and its health benefits only appear in the future. we collected the participants' demographic information, such as household size, monthly family income, education level, age, gender, and health status.

In stage two, we conducted random SMS interventions, which proceeded as follows. The households that participated in the survey were randomly assigned to one of four arms: the control group and three treatment groups. Households in the control group received no SMS from us, and those in the three treatment groups received one of the following daily SMS interventions over an eight-day period:

Cost SMS Treatment. We provided the households in the group with their actual daily electricity expenses, as well as their weekly expenses on the last day of the SMS intervention. Individual households' electricity expenses were obtained from the local electricity company. An example of a Cost SMS is as follows: *To help you understand the cost of heating, here is an update on your daily electricity consumption. Yesterday (Feb 19, 2019), you consumed 6 kilowatt hours (kWh), which costs RMB3.4. [ShanghaiTech University research group]*

Health SMS Treatment. we provided scientific evidence of the various types of coal heating-related health issues. Each day, we provided information on a specific type of health issue. The scientific evidence we shared was based on research findings documented in the medical literature. An example of a Health SMS is as follows: *Electric heating is environmentally friendly and clean. Scientific evidence suggests that burning coal on average increases the chance of developing respiratory diseases by 36% relative to other clean technologies. For your family's* *health, please use electric heating. [ShanghaiTech University research group]*

Social Comparison SMS Treatment. We provided the information of the percentages of households in neighboring villages that had transitioned from coal-burning stoves to electric heating devices. These percentages were derived from self-reported preferences and heating choices of villagers residing in other villages within the same geographical area as our sample population. An example of a Social Comparison SMS is as follows: *Electric heating is actually very simple and many residents have switched to electric heating. According to our survey, 56.7% of residents in village A have switched to electric heating. Please join this new, environmentally friendly movement. [ShanghaiTech University research group]*

3.2 Sampling and Randomization

We conducted the experiment in two villages that are representative in terms of population size and average annual per capita income from a list of 114 villages in the same county.[7] At the beginning of our pre-treatment survey, we extended invitations to household members who were present at home to participate in the survey interviews. To raise awareness about our survey, we collaborated with village heads who broadcasted announcements, as they serve as the primary source of information dissemination within these villages. This approach helped establish a sense of trust and credibility, ensuring that participants perceived our SMS campaigns as reliable. The survey interviews were conducted on January 25, 2019, and a total of 268 households' members were interviewed.

For the second stage of SMS interventions, our sample households were selected from the participants who took part in the stage one interviews. Prior to the randomization, we excluded survey participants who provided incorrect contact details or electricity meter numbers, as it would have been impossible to send SMS messages to these individuals and monitor their electricity consumption. Additionally, we excluded participants who reported having installed an excessive number of heaters (more than 10), as this indicated a high likelihood of being an organization, such as a kindergarten. After these exclusions, the final sample size for the SMS interventions consisted of 243 households.

The survey participants were assigned randomly to four groups: one control group and three treatment groups, which corresponded to the three SMS interventions described earlier. The randomization process followed the standard procedure outlined in prior research (Duflo et al., 2007). Stratification was employed using three characteristics obtained from the pre-treatment survey: participants' preference for coal heating, whether they overestimated their electricity expenses, and whether they underestimated the health damages associated with coal heating. As a result of this procedure, the control group comprised 70 households, while the Cost SMS, Health SMS, and Social Comparison SMS groups consisted of 54, 71, and 48 households, respectively.

[7] The two villages are representative in terms of their population size and income level. One village has a population of 3,208 with 760 households, and the other has a population of 1,800 with 374 households. The two villages are located in the same township, and the annual per capita disposable income is RMB 13,260 (≈ US$ 2,051), which is the median level across villages in the same country (Statistics Bureau of Anyang, 2018).

4 Data

4.1 Sample Statistics

Table 1 presents the baseline characteristics of households, as obtained from the pre-treatment survey. The summary statistics are categorized into five groups. The first category focuses on participants' stated preferences for heating methods. It is notable that more than 40% of participants in each treatment group expressed a preference for coal heating. The second and third categories present the participants' estimations of electricity expenses and the health damage associated with coal heating. The majority of participants exhibited an overestimation bias toward electricity expenses (over 80% in each group) and an underestimation bias toward the health damage caused by coal heating (approximately 70% in each group). These perception biases are further discussed in Subsection 6.1. The fourth category examines the ranking of factors that influence the choice of a heating method among participants. The factors considered include price, health impact, environmental impact, and the choices of neighbors. The most frequently mentioned factors were price and health impact, while the choices of neighbors were least mentioned.

The fifth category provides information on the socioeconomic and demographic variables in our sample, including the participants' age, gender, education level, monthly family income, household size, number of installed heaters, awareness of electricity prices, current self-evaluated health status (compared to the previous year and compared to their peers), and time preference. The participants had an average age of 52, with a majority of them being men. Furthermore, approximately 90% of the participants had received primary school education, indicating a high literacy rate among the villagers. Around 53% of the households reported a relatively low monthly income of approximately RMB 2,000 (US$ 308). The average household size was approximately four people. On average, participants reported having three electric heaters at home, but only 35% of them were aware of the cost of electricity. Most participants perceived themselves to be healthier than their peers, but they felt that their own health had declined compared to the previous year. Surprisingly, the majority of participants (81%) did not exhibit present bias.

Finally, the last column of Table 1 displays the p-values for testing the equality of means between the control group and the combined treatment groups. The baseline characteristics of the treatment and control groups exhibit no statistically significant differences for most variables, indicating that the randomization process was effective.

Table 1: Summary statistics for each group

	Mean and Std. Dev.				
	Control	Cost SMS	Health SMS	Social Comparison	p-value
1. Preference					
Prefer coal heating	0.51 (0.50)	0.41 (0.50)	0.43 (0.50)	0.47 (0.50)	0.28
2. Estimation of electric heating expenses					
Overestimate energy cost	0.87 (0.34)	0.80 (0.40)	0.88 (0.33)	0.83 (0.38)	0.59
3. Estimation of health damage from coal heating					
Underestimate health damage	0.74 (0.44)	0.69 (0.47)	0.72 (0.45)	0.73 (0.45)	0.62
4. Factors that villagers view as important when choosing a heating method					
Price	0.50 (0.50)	0.46 (0.50)	0.59 (0.50)	0.54 (0.50)	0.60
Health impact	0.53 (0.50)	0.44 (0.50)	0.45 (0.50)	0.50 (0.51)	0.35
Environmental impact	0.34 (0.48)	0.43 (0.50)	0.44 (0.50)	0.40 (0.49)	0.26
Neighbours' decisions	0.07 (0.26)	0.17 (0.38)	0.11 (0.32)	0.17 (0.38)	0.12
5. Socio-economic and demographic variables					
Age	53.1 (12.0)	53.0 (13.9)	52.4 (12.5)	50.9 (13.2)	0.61
Female	0.31 (0.47)	0.29 (0.46)	0.20 (0.41)	0.15 (0.36)	0.12
Attended primary school	0.93 (0.26)	0.88 (0.33)	0.90 (0.30)	0.91 (0.28)	0.49
Income high($\geq 2,000$RMB)	0.60 (0.49)	0.53 (0.50)	0.53 (0.50)	0.43 (0.50)	0.15
Household size	4.65 (1.81)	4.28 (2.00)	4.93 (1.68)	3.83 (1.59)	0.39
Number of heaters	2.73 (2.70)	2.41 (3.34)	2.55 (2.30)	2.02 (1.42)	0.33
Know electricity price	0.40 (0.50)	0.45 (0.50)	0.23 (0.43)	0.30 (0.47)	0.30
Healthier than peers	2.81 (1.16)	2.76 (1.18)	2.64 (1.27)	2.81 (1.33)	0.62
Healthier than last year	2.28 (0.51)	2.12 (0.60)	2.25 (0.67)	2.26 (0.53)	0.43
Present bias	0.19 (0.39)	0.17 (0.38)	0.21 (0.41)	0.17 (0.38)	0.99
Sample size	70	54	71	48	

Note: Standard deviations are shown in parentheses. The P-values test the equality between the control and the pooled treatment groups.

4.2 Measurement of Electric Heating Consumption

To analyze household responses to the SMS interventions, we use changes in electricity consumption as a proxy for changes in electric heating usage. Specifically, we use each household's average daily electricity consumption in October 2018 as a benchmark, as this is the month immediately preceding the season in which most people begin to heat their homes. As a result, electricity consumption in October is mostly associated with energy demands other than heating. To measure the participants' electricity consumption for heating needs, referred to as the "electric heating consumption" in the rest of the paper, we use the difference in the participants' daily electricity consumption in the heating season and the corresponding average daily consumption in October.

We obtained administrative data on the household-level daily electricity consumption from the local energy utility company for the following periods: January 1 to 27 and February 18-March 28, 2019.[8] These include four weeks of daily consumption data before the SMS interventions, and six weeks of daily consumption data after the interventions. Our eight-day SMS intervention was conducted during the fifth week, February 18-25. We obtained monthly electricity consumption data in October 2018 as the baseline electricity consumption unrelated to heating, which we use to calculate households' electric heating consumption for later dates. We also obtained households' monthly electricity consumption for the period from October 2019 to March 2020, which allows us to track the potential long-term treatment effects of the SMS interventions.

5 Empirical Strategy and Estimation Validity

5.1 Empirical Strategy

To assess whether our SMS interventions result in an increased demand for electric heating, we use a standard Difference-in-Difference (DID) regression methodology by comparing the electric heating consumption of individual households in the treatment groups with that of the control group before and after the SMS interventions. We sent SMS to the participants between February 18 and 25, 2019 (one week). The pre-treatment period was January 1 to 27, 2019 (four weeks), and the post-treatment period was February 18 to March 28, 2019 (six weeks).

First, we estimate the average treatment effect using the following regression model:

$$Y_{ijt} = \beta_0 + \sum_{k=1}^{3} \beta_k \times T_k \times Post_t + \gamma \mathbf{X}_i + \alpha_j + \delta_t + \varepsilon_{ijt}, \tag{1}$$

where the dependent variable Y_{ijt} is the level of electric heating consumption for household i in village j on day t, which is defined as the difference between daily consumption in the winter heating period in 2019 and average daily consumption in October 2018. T_1, T_2, and T_3 are indicator variables that equal 1 if the household is in the Cost SMS, Health SMS, and

[8] Observations in the period from January 28 to February 17, 2019 are omitted, as they overlap with the Chinese New Year holiday and the Lantern Festival. Electricity consumption during this period is associated with various celebrations and activities for the spring festival. As this does not represent a typical period during the cold season, including it in the analysis may bias our results.

Social Comparison SMS treatment groups, respectively, and 0 for the control group. *Post* is a dummy variable that equals 1 for the post-treatment period (February 18–March 28, 2019), 0 for the pre-treatment period (January 1 to 27, 2019). $\mathbf{X}_{ij}$ is a vector of household-level control variables, as listed in Table 1.[9] α_j is the village fixed effects, which is used to absorb the differences in electric heating at the village level. δ_t is the day fixed effects, which is included to absorb weather variations as well as other unobserved concurrent factors. β_1, β_2, and β_3 in equation (1) are our key parameters of interest. These variables capture the average treatment effect of receiving Cost SMS, Health SMS, and Social Comparison SMS, respectively, on electric heating activities by comparing the changes of the electricity heating consumption before and after the SMS provision for the treatment households relative to the changes in the control group.

When designing the pre-treatment survey, we anticipate that there may be potential heterogeneous responses to the SMS interventions depending on various factors, such as the extent of households' misperception about the cost associated with electric heating, the health damages from coal heating, etc. We posit that households that overestimate the costs associated with electric heating (respectively, underestimate the potential health damage of coal heating) may respond more strongly to the Cost SMS (respectively, Health SMS) than their counterparts, because the interventions help correct these misperceptions. In addition, if households do not seem concerned about the cost of heating, the potential health impact, or the heating choices of others, they would be less affected by the corresponding SMS intervention.

The effects of the Cost and Health SMS campaigns are also expected to be greater for affluent and educated households, as individuals in these categories are more likely to possess the necessary skills to process the information and have the means to switch to the more expensive electric heating. As such, we further explore the heterogeneity of each SMS treatment effect by estimating the average treatment effect for each household comparison group separately.

We analyze the heterogeneity of each SMS treatment effect by running the following group specific DID regression equations:

$$Y_{ijt} = \beta_0 + \beta_g \times T_k \times Post_t + x_i + \alpha_j + \delta_t + \varepsilon_{ijt}, \tag{2}$$

where g stands for a subsample of households, and $k = \{1, 2, 3\}$ such that T_1, T_2, and T_3 are indicators for the Cost SMS, Health SMS, and Social Comparison SMS treatment groups, respectively; and x_i is household fixed effects. For example, to investigate the heterogeneous treatment effects of the Cost SMS among households with overestimations of electricity expenses, we estimate equation (2) using subsamples of those who overestimated and those who did not overestimate their electricity expenses in the control group and the Cost SMS treatment groups in two separate regressions. We then compare the difference between β_g and $\beta_{g'}$ by using the combined subsample with triple differences between the treatment dummy, *Post*, and a dummy variable for whether household i belongs to group g; specifically, we estimate:

$$Y_{ijt} = \beta_0 + \beta_d \times T_k \times Post_t \times \mathbb{1}_{i \in g} + \beta_k T_k \times Post_t + x_i + \alpha_j + \delta_t + \varepsilon_{ijt}. \tag{3}$$

[9] We also replace the household-level control variables with household fixed effects in another specification to absorb the effects of household characteristics.

If the coefficient β_d is statistically significant, it indicates that the treatment effect of the Cost SMS campaign varies significantly between households in group g and those not in group g regarding their electric heating expenses.

5.2 Estimation Validity: Parallel Trends

To validate our DID estimation strategy, we examine the trends in electric heating activities over time for both the control and treatment groups during the pre-treatment period. We employ an event study approach by dividing the pre-treatment period into five weeks and the post-treatment period into six weeks. We then compare the treatment effect for each week individually using the following equation:

$$Y_{ijt} = \beta_0 + \sum_{t=-4}^{5} \beta_{1,t} \times T_1 \times W_t + \sum_{t=-4}^{5} \beta_{2,t} \times T_2 \times W_t + \sum_{t=-4}^{5} \beta_{3,t} \times T_3 \times W_t + x_i + \alpha_j + W_t + \varepsilon_{ijt}, \tag{4}$$

where the dependent variable Y_{ijt} is the weekly mean electric heating consumption of household i in village j in week t; x_i is household fixed effects, used to absorb differences in household characteristics; and W_t is week fixed effects, used to capture time variations in heating activities. W_{-1} is the week immediately preceding the treatment and is omitted as the baseline period (see Jaravel et al., 2018 and Autor et al., 2006 for the selection of the baseline period). The coefficients of $(\beta_{k,-4}, ..., \beta_{k,-2})$, $k \in 1,2,3$, measure the difference in electric heating consumption between treatment group k and the control group four, three, and two weeks before the treatment relative to the difference in the week just preceding the treatment. Similarly, the coefficients $\beta_{k,0}, ..., \beta_{k,5}$, $k \in 1,2,3$, are the analogous estimates for each of the six post-treatment weeks.

Figure 1 displays the estimated coefficients $(\beta_{k,-4}, ..., \beta_{k,-2}, \beta_{k,0}, ..., \beta_{k,5})$, $k \in \{1,2,3\}$, for specification 4, along with their corresponding 95% and 90% confidence intervals. Notably, none of the pre-treatment coefficients are statistical significant, providing support for the validity of the DID estimation strategy described in Section 5.1. Furthermore, upon visual inspection of the post-treatment period, it appears that the Cost SMS treatment has a noticeable negative effect, while the Health SMS and Social Comparison SMS treatments do not exhibit economically significant effect on electric heating consumption.

6 Results

6.1 Stylized Facts

Overestimation of Electricity Expenses. To measure whether and to what extent households overestimate electric heating costs, we incentivized the study participants by offering a monetary reward. The participants were asked to estimate their electricity bill for the day before the survey (January 24, 2019), and a reward of RMB 5 ($\approx$ US\$0.76) was provided to those who provided an accurate estimate. Panel (a) of Figure 2 shows the kernel estimate of the distribution of the estimated and actual electricity expenses; it shows that the distribution

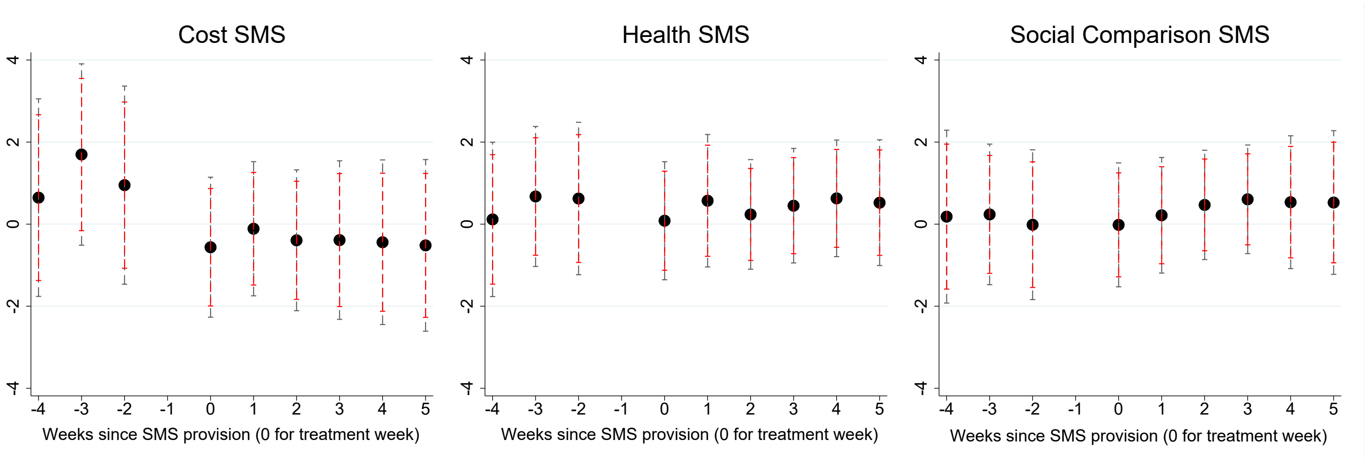


Figure 1: Pre-trends in Electric Heating Consumption (weekly means)

Note: Estimates based on ordinary least squares (OLS) regressions (Equation (4)). The three figures show the difference in electric heating consumption between the respective treatment and control groups by week, in which the week immediately preceding the SMS interventions is omitted as the baseline period. In all of the regressions, we control for village fixed effects, individual household fixed effects, and week fixed effects. The dotted red and grey bars represent the 95 % and 90 % confidence intervals, respectively.

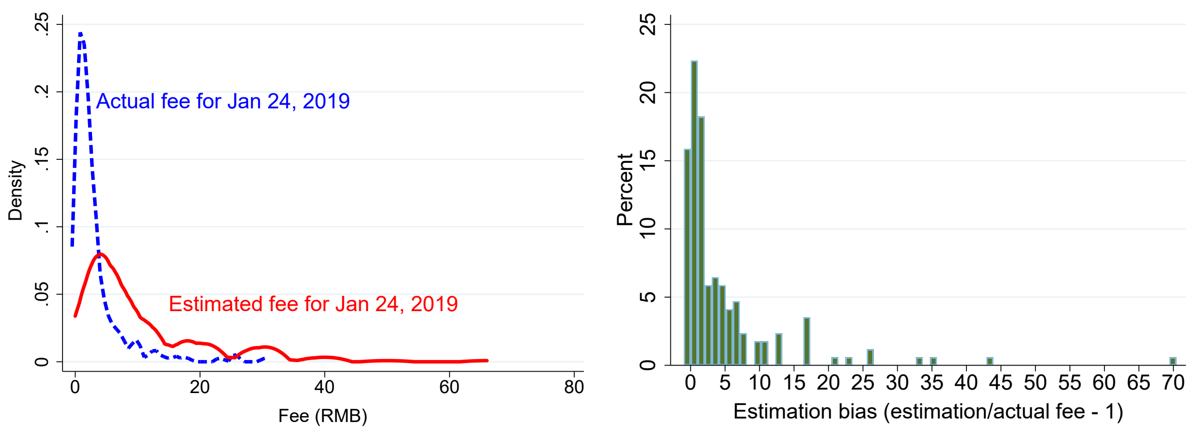
of the estimated expenses is rightward shift of the distribution of the actual expenses. In fact, 84.8% of the survey participants overestimated their electricity expenses.[10] We also calculate the *estimation bias*, which is defined to be $Estimated\ Expense/Actual\ Expenses - 1$. Panel (b) of Figure 2 plots the histogram of the estimation bias, which reveals that among those who overestimated their energy costs, more than 73% overestimated by more than 100%. Figure 2 provides clear evidence that most households substantially overestimated their electricity expenses.

Stylized Fact 1: *A large proportion of the households overestimate their electricity expenses to a great extent.*

Underestimation of the Health Damage Associated with Coal Heating. In our pre-treatment survey, we used the following question to elicit households' perceptions of the potential health damage associated with coal heating.

"Studies show that air pollution levels in the north caused by coal heating greatly exceed the levels found in the south. Do you think this has an impact on life expectancy in the north and the south?
a. No impact
b. Life expectancy in the north is 0.5 years shorter
c. Life expectancy in the north is 1 year shorter
d. Life expectancy in the north is 3 years shorter
e. Life expectancy in the north is 5 years shorter"

[10] In a non-incentivized question, we asked the participants to estimate their average monthly electricity bill during the heating season. More than 92% of the participants overestimated their monthly electricity expenses.



(a) Estimating Expenses on January 24, 2019

(b) Estimation Bias

Figure 2: Estimation of Electricity Expenses

Notes: Figure (a) plots the kernel density estimates of households' actual and estimated electricity fees for January 24, 2019. Figure (b) plots the histogram of households' overestimation bias.

A strand of the empirical evaluation literature has demonstrated the adverse impact of air pollution on life expectancy in China, specifically in relation to the Huai River Policy. This policy offers heavily subsidized coal for indoor heating during the winter months to cities located north of the *Huai* River, while cities to the south of *Huai* river do not receive this benefit. Notably, studies by Chen et al. (2013) and Ebenstein et al. (2017) found that prolonged exposure to air pollution resulting from coal heating in the northern regions leads to a reduction in life expectancy by approximately 3 to 5.5 years. Building upon these findings, we categorize survey participants who selected options "no difference," "0.5 years," or "1 year" in response to the survey question mentioned above as belonging to the underestimation group.

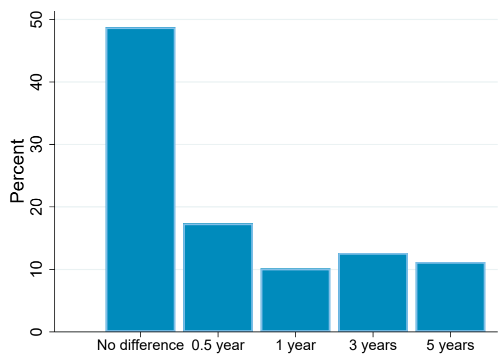


Figure 3: Beliefs About Life Expectancy Reductions as a Result of Coal Heating

Figure 3 depicts the histogram of the participants' responses to the aforementioned question. The histogram reveals that a significant majority, approximately 75.4%, of the participants, underestimated the health damages from coal heating. In fact, the mode choice is "no difference," with about 48%, as shown in Figure 3. These findings serve as compelling evidence that the majority of households possess inadequate awareness and understanding regarding the potential health consequences of coal heating.

Stylized Fact 2: *The majority of households underestimate the health damage of coal heating.*

Present Bias. To assess subjects' time preferences, we conducted two sets of tasks. In the first set, participants were given the choice between receiving RMB 40 after a month of waiting, or a lower amount ranging from RMB 35 to RMB 10 immediately. In the second set, participants had to choose between receiving RMB 40 in seven months or a lower amount ranging from RMB 35 to RMB 10 in six months. Through these tasks, we estimated the discount factors for each participant. To determine if participants exhibited present bias, we compared their discount factors between the two sets of tasks. If the discount factor in the first task was lower than the second task, the participant was classified as present-biased. Interestingly, we found that participants who displayed present bias were not significantly more likely to prefer coal heating. Specifically, among the present-biased participants, 35% preferred coal heating, which was not significantly different from the 47% preference among those who were not present-biased (with a p-value of 0.11).

Stylized Fact 3: *Present-biased participants are not more likely to prefer coal heating.*

6.2 Determinants of Heating Preference

Using the survey data, we examine the factors that influence heating preferences based on the characteristics outlined in Table 1. Our analysis reveals compelling findings regarding the motivating factors associated with coal heating preference.

Firstly, participants who considered the price factor as important were significantly more inclined to prefer coal heating, with 57% expressing a preference for coal heating compared to 31% among those who did not consider price important. This difference is statistically significant, with a p-value of 0.00 based on a two-sample t-test. Furthermore, participants who overestimated their electricity expenses were also more likely to favor coal heating compared to those who did not overestimate electricity expenses, although the p-value of 0.09 under a two-sample t-test falls just short of conventional statistical significance.

Participants who viewed health factor important were significantly less likely to prefer coal heating (28%) than those who do not (62%), and the difference is significant with p-value equal to 0.00. However, participants who underestimated health damage of coal heating were not significantly more likely to prefer coal heating (44%) than those who did not (47%). Participants who viewed environment factor important were significantly less likely to prefer coal heating (29%) than those who did not (56%), and the difference is significant with p-value equal to 0.00. Participants who viewed neighbors' decisions important were significantly more likely to prefer coal heating (59%) than those who did not (43%), and the difference is significant with p-value equal to 0.00.[11]

Table 2 presents the average marginal effects estimated from the Probit regressions, where the dependent variable is assigned a value of 1 if a participant indicated a preference for coal

[11]The proportion of participants who considered the price factor, the health factor, the environment factor, and neighbors' decision important are 52%, 48%, 41%, and 12%, respectively.

heating and 0 otherwise. The analysis focuses on several key independent variables, including misperceptions related to energy cost and health damage, as well as other factors that households may consider important when deciding on a heating method.

Regarding cost-related factors, two dummy variables are utilized. The first, "Overestimate energy costs," equals 1 if a participant overestimated their electricity expenses on January 24, 2019. The second, "Price," equals 1 if a participant considered price as an important factor in their heating method selection.

In terms of health-related factors, three dummy variables are employed. The first, "Underestimate health damage," equals 1 if a participant belonged to the underestimation group regarding health damage caused by coal heating. The second, "No impact on life expectancy," equals 1 if a participant believed that there was no health impact associated with coal heating at all. The third, "Health impact," equals 1 if a participant considered health as an important factor in their heating method selection. Additionally, the variable "Neighbors' decisions" takes a value of 1 if a participant believed in and tended to follow the choices of their neighbors.[12]

Table 2 reveals two main correlation patterns regarding coal heating preferences. Firstly, in terms of health impact, households that prioritize health or the environment are significantly less likely to prefer coal heating. However, underestimating the health damage associated with coal heating does not exhibit a strong association with heating preference. Secondly, from a cost perspective, there is no significant relationship between overestimating electricity expenses and heating preference.[13] The coefficient of "Price" is positive but lacks strong significance. These correlation patterns suggest that individuals make heating method selections based on their personal values rather than their misperceptions.

In addition, the coefficients of the demographic variables in Table 2 provide additional insights. It shows that households that reported owning a larger number of electric heaters tended to use these heaters more frequently. Participants with relatively higher income levels were found to be less likely to choose coal heating, while female participants showed a greater preference for coal heating than male participants. Interestingly, we do not observe a significant association between present bias and heating preference, suggesting that the preference for coal heating is not related to present bias.

[12] Additional independent variables included in the analysis are as follows. The dummy variables "Healthier than peers" and 'Healthier than last year," take a value of 1 if a participant's self-evaluated health status was better than that of their peers, and better than their own health in the previous year, respectively. A dummy variable "Environmental impact" takes value 1 if the subject considered environment an important factor in the heating method selection. A dummy variable "Know electricity price," takes value 1 if the participant was aware of the cost of electricity. The dummy variable "Present bias" takes value 1 if the participant's time preference exhibit present bias. Furthermore, the analysis controls for demographic information, including the size of households, the number of installed heaters, education level, income, age, and gender. In total, we have three specifications. When an independent variable has missing observation, we either drop observations with missing data (specification 1), set the missing data to 0 (specification 2), or use the corresponding village mean (specification 3), and include indicators for missing data in both specifications 2 and 3.

[13] It is worth noting that when we replace the "Overestimate energy cost" dummy with measures such as the degree of overestimation (i.e., $\mathit{Estimated\ Expense} - \mathit{Actual\ Expense}$) or estimation bias (i.e., $\mathit{Estimated\ Expense}/\mathit{Actual\ Expenses} - 1.$), the results remain consistent.

Table 2: Heating Preference and Related Factors

	Prefer Coal Heating		
	(1)	(2)	(3)
Overestimate energy costs	-0.095	-0.015	-0.025
	(0.097)	(0.083)	(0.083)
Underestimate health damage	-0.093	-0.045	-0.042
	(0.112)	(0.084)	(0.084)
No impact on life expectancy	0.016	0.043	0.043
	(0.088)	(0.070)	(0.071)
Price	0.143*	0.092	0.092
	(0.083)	(0.065)	(0.065)
Health impact	-0.267***	-0.229***	-0.229***
	(0.077)	(0.055)	(0.055)
Environmental impact	-0.194**	-0.184***	-0.184***
	(0.079)	(0.059)	(0.059)
Neighbours' decisions	0.069	0.091	0.090
	(0.122)	(0.091)	(0.091)
Age	0.001	-0.003	-0.003
	(0.003)	(0.003)	(0.003)
Female	0.219**	0.018	0.017
	(0.090)	(0.070)	(0.070)
Attended primary school	-0.095	-0.037	-0.037
	(0.161)	(0.092)	(0.092)
Income high	-0.056	-0.192***	-0.192***
	(0.085)	(0.061)	(0.061)
Household size	0.017	0.022	0.022
	(0.022)	(0.018)	(0.018)
Number of heaters	-0.032***	-0.056***	-0.056***
	(0.012)	(0.016)	(0.016)
Know electricity price	-0.071	-0.062	-0.056
	(0.077)	(0.071)	(0.071)
Healthier than peers	0.014	0.041*	0.042*
	(0.030)	(0.024)	(0.024)
Healthier than last year	0.031	0.048	0.048
	(0.072)	(0.058)	(0.058)
Present bias	-0.032	-0.089	-0.088
	(0.095)	(0.075)	(0.075)
Obs.	143	232	232
Pseudo R^2	0.238	0.231	0.230
Sample	Drop missing observations	Replace missing with 0, and add missing indicators	Replace missing with village mean, and add missing indicators

Note: The reported coefficients are the average marginal effects of the Probit regressions. "Attended primary school" is a dummy variable that equals 1 if a survey participant had at least finished primary school, and "Income high" is a dummy variable that equals 1 if a household's overall monthly income is at least RMB 2,000 (US$ 308). Standard errors reported in parentheses are clustered at the individual household level. Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

6.3 Effects on Electric Heating

We begin by estimating the average treatment effects of the SMS interventions on electric heating consumption, and then explore the heterogeneity of each treatment with different types of households. Finally, we explore the potential long-term treatment effects.

6.3.1 Average Effects

Table 3 reports the DID estimators (β_k's) of Equation (1) for the four specifications using daily electric heating consumption at the household level in the pre-treatment period (i.e., January 1 to 27, 2019) and post-treatment period (i.e., February 18–March 28, 2019). Specifically, Column 1 includes day fixed effects and village fixed effects, and Columns 2 and 3 add individual control variables, as listed in Table 1. When there are missing observations for the control variables, we include the full sample by replacing the missing observations with either 0 (Column 2) or the village means (Column 3), while including controls for the missing variables. Moreover, in Column 4 we replace the control variables with individual household fixed effects to absorb the effects of household characteristics.[14]

In Column 1, the coefficient of "Cost SMS×Post" shows that the households who received feedback on their electricity consumption consumed approximately 1.23 fewer kWh per day, relative to those that received no information, with significance at the 1% level. This is equivalent to a reduction of 52% below the average daily electric heating consumption of the control group during the pre-treatment period (2.36 kWh per day). In contrast, the coefficients of "Health SMS×Post" and "Social comparison SMS×*Post*" are not statistically significant, despite having positive values. In other words, the average effect of Health and Social Comparison SMS treatments for the full sample is almost unchanged after controlling for an extensive list of household characteristics or individual fixed effects (Columns 2–4). We also explore the dynamic process of the average treatment effects in the six-week post-treatment period by conducting another event study, and find similar results (see Appendix A).

Result 1: *On average, the Cost SMS has a statistically significant effect in reducing the electric heating usage. Both the Health SMS and Social Comparison SMS do not have a significant effect on electric heating usage.*

We now assess the reasons why the Cost SMS does not yield the expected result (that providing accurate information about electricity expenses will correct any overestimation bias and thus increase electric heating usage levels). One explanation is that the effect of Cost SMS works in two opposing directions. Firstly, the Cost SMS may indeed help correct the overestimation bias, leading households to consider using electric heating more frequently. However, it is also plausible that the Cost SMS has an unintended consequence. Sending the SMS may increase households' attention (Sims, 2003) to the cost aspect, making the electricity expenses more salient. Previous studies (Sims, 2003; Chetty et al., 2009; Finkelstein, 2009; Brown et al., 2010; Lacetera et al., 2012; Tiefenbeck et al., 2018) discussed the influence of salience bias on decision-making processes. The observed results are also in line with the notion that households

[14] We also repeat all of the regression analyses, controlling for households' electricity consumption in October 2018, which we use as the baseline consumption, and find similar results.

Table 3: Average Treatment Effects on Electric Heating

	Electricity Consumption for Heating			
	(1)	(2)	(3)	(4)
Cost SMS × Post	-1.235***	-1.230***	-1.230***	-1.231***
	(0.351)	(0.331)	(0.331)	(0.247)
Health SMS × Post	0.016	0.023	0.023	0.011
	(0.270)	(0.263)	(0.263)	(0.201)
Social Comparison SMS × Post	0.262	0.269	0.269	0.282
	(0.280)	(0.272)	(0.272)	(0.205)
Day fixed effects	Yes	Yes	Yes	Yes
Village fixed effects	Yes	Yes	Yes	Yes
Control variables	No	Yes	Yes	No
Household fixed effects	No	No	No	Yes
Obs	14,834	14,834	14,834	14,834
Adjusted R^2	0.052	0.107	0.108	0.453

Note: Robust standard errors are reported in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

may have a negative perception of paternalistic SMS interventions, and as a result they might resist the external interventions that aim to influence their behavior. From a policy standpoint, the finding suggests that information nudges may have unintended consequences.

6.3.2 Heterogeneity

The average treatment effects, however, may obscure possible heterogeneity in households' perceptions and interests in the issue. To explore these heterogeneous effects, we employ the estimation strategy outlined in Equation (2) on sub-samples of households. In all of the estimations, the key parameter of interest is the DiD estimator. The heterogeneous treatment effects are reported in Table 4, in which the bottom line of each panel reports the differences between the two DiD estimators in each paired category, and the p-values for the differences are estimated using the combined sub-samples with interactions between the treatment dummy, the post-treatment dummy, and the respective category dummy, analogous to Equation (3).

Heterogeneity of Cost SMS. When considering the effects of the Cost SMS, households with cost overestimation would be less inclined to use electric heating. Additionally, households that prioritized the price factor when selecting a heating method would be more responsive to the the Cost SMS compared to those who do not consider price a significant decision factor. Moreover, households with higher monthly incomes, indicating fewer financial constraints, would be more willing to adopt electric heating. For these reasons, we classify the control and Cost SMS treatment groups into three paired categories: (1) whether electricity expenses were overestimated; (2) whether price was viewed as an important factor when choosing a heating method; and (3) whether monthly income was above the median level (RMB 2,000).

Table 4: Heterogeneous Treatment Effects on Electric Heating

Panel A: Heterogeneous Treatment Effects of Cost SMS

	Overestimate electricity cost		Price Concern		Monthly income ⩾ RMB2,000	
	(Yes)	(No)	(Yes)	(No)	(Yes)	(No)
	(1)	(2)	(3)	(4)	(5)	(6)
Cost SMS×Post	-0.170	-8.325***	-2.509***	-0.007	-1.022***	-2.405***
	(0.209)	(1.300)	(0.387)	(0.312)	(0.362)	(0.373)
Obs.	5,056	960	3,710	3,902	4,161	3,005
Adjusted R^2	0.471	0.475	0.509	0.452	0.488	0.489
Fixed effects: Day, Village, household						
Difference [p-value]	8.155***	[0.000]	-2.502***	[0.000]	1.383***	[0.008]

Panel B: Heterogeneous Treatment Effects of Health SMS

	Underestimate health damage		Health Concern		Monthly income ⩾ RMB2,000		Attended primary school	
	(Yes)	(No)	(Yes)	(No)	(Yes)	(No)	(Yes)	(No)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Health SMS×Post	-0.333	0.95***	0.934***	-0.928***	0.451	-0.624**	0.238	-2.009***
	(0.242)	(0.359)	(0.284)	(0.270)	(0.288)	(0.263)	(0.215)	(0.531)
Obs.	6,395	2,300	4,215	4,480	4,857	3,647	7,736	768
Adjusted R^2	0.461	0.320	0.528	0.308	0.506	0.265	0.448	0.297
Fixed effects: Day, Village, household								
Difference [p-value]	-1.283***	[0.003]	1.862***	[0.000]	1.075***	[0.006]	2.247***	[0.000]

Panel C: Heterogeneous Treatment Effects of Social Comparison SMS

	Cared about neighbours' heating choices	
	(Yes)	(No)
	(1)	(2)
Social Comparison SMS×Post	2.756***	0.027
	(0.867)	(0.208)
Obs.	768	6,459
Adjusted R^2	0.24	0.506
Fixed effects: Day, Village, household		
Difference [p-value]	2.729*** [0.002]	

Note: The difference between the coefficients in each paired category (Panel A: Column 1 vs. 2, Column 3 vs. 4, and Column 5 vs. 6; Panel B: Column 1 vs. 2, Column 3 vs. 4, Column 5 vs. 6, and Column 7 vs. 8; Panel C: Column 1 vs. 2) are reported in the last row of each panel, and p-values for the differences are shown in brackets. Robust standard errors are reported in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Columns 1 and 2 of Panel A reveal significant and contrasting effects of the Cost SMS interventions. The effect is notably larger and significantly negative for households that did not exhibit cost overestimation compared to those with cost overestimation. Given stylized fact 1, which highlights the prevalence of households to overestimate electricity expenses, the non-significant effect observed among households with cost overestimation can be attributed to motivated belief. These households may derive utility from maintaining their biased belief, which motivates them to strategically disregard the Cost SMS intervention and sustain lower levels of electric heating usage. This finding is also consistent with the view that this group of households may be hostile towards paternalistic interventions.

Columns 3 and 4 of Panel A show that those who reported that price was an important factor in their heating preference decision reduced their electric heating consumption significantly after receiving the Cost SMS. In addition, Columns 5-6 show that the Cost SMS leads to a decrease in electric heating usage across all income levels, although households with below-median income (Column 6) exhibited a greater responsiveness to the SMS campaign. These findings suggest that the salience effect of the Cost SMS is particularly pronounced for households who were concerned about costs. These individuals may pay closer attention to the electricity expenses, leading to a negative average treatment effect of Cost SMS. Taken together, the results from Panel A of Table 4 suggests that debiasing the overestimation of electricity cost through the Cost SMS intervention was not an effective approach to promote electric heating usage. This is because cost concerns can trigger households to focus on the salience of electric heating expenses, inadvertently causing the Cost SMS campaign to have negative effects.

Result 2: *The Cost SMS intervention does not have a significant effect on the adoption of electric heating among households with cost overestimation. However, for households that prioritize cost considerations, the Cost SMS intervention leads to a reduction in electric heating usage.*

Heterogeneity of Health SMS. The impact of the Health SMS intervention may differ based on individuals' perception of health damage caused by coal heating and their consideration of health as a significant factor when choosing a heating method. In addition, the responses to the Health SMS may vary depending on the recipients' education and income levels. It is expected that households with higher education and income levels are more likely to understand the importance of the potential health impacts associated with coal heating, which could facilitate their transition to electric heating. As such, we classify the control and Health SMS treatment groups into four paired categories.

In Panel B, Columns 1 and 2 highlight the effects of the Health SMS intervention. It shows that among households who had a clear understanding of the potential health damage associated with coal heating, the Health SMS intervention resulted in a significant increase of 55.8% in the uptake of electric heating compared to their baseline consumption, which was 1.7 kWh per day in the pre-treatment period. Surprisingly, no significant effect is found for households that underestimated the health damage. This finding can be attributed *motivated belief*, wherein households that underestimated the health damages of coal heating may consciously maintain their biased beliefs in order to minimize their anxiety related to health concerns.

In Columns 3-4 of the analysis, it is observed that households who considered health as an important factor in their heating choices increased their electric heating usage by 0.934 kWh per day, representing a significant 25.6% increase compared to their baseline consumption of 3.65 kWh per day, after receiving the Health SMS. Contrastingly, a significant negative effect is found among households who did not prioritize health as a factor. This group exhibited a 25.4% decrease in electric heating usage after receiving the Health SMS. Similar negative effects were also observed among households with a monthly income exceeding RMB 2,000 and households with less than primary education. These results indicate that the Health SMS intervention backfired for these specific groups of households. It is possible that these households were motivated to maintain their existing beliefs, or they might exhibit an aversion toward paternalistic interventions.

Result 3: *The Health SMS has no significant impact on households that underestimated the health damage caused by coal heating. However, it has a significant negative effect on households that did not attach importance to health concern of coal heating. For households that correctly understood the health damage of coal heating or considered health as an important factor in their heating choices, the Health SMS intervention has a significant positive effect.*

Heterogeneity of Social Comparison SMS. In Panel C of Table 4, the heterogeneous effects of the Social Comparison SMS are presented, focusing on individuals who expressed concern about their neighbors' heating choices. It is observed that the Social Comparison SMS intervention has a significant effect only among those who reported being concerned about their neighbors' choices.[15] It is worth noting that only 12% of the sample population expressed concern about their neighbors' heating decisions, as indicated in Table 1. This suggests that the majority of the participants made their heating decisions without considering their neighbors' choices. Therefore, the lack of statistical significance in the average treatment effect of the Social Comparison SMS in Table 3 is not unexpected, given the limited proportion of individuals who were influenced by their neighbors' heating choices.

Result 4: *The Social Comparison SMS has a significant positive effect on electric heating only among households that reported being concerned about their neighbors' heating choices.*

6.4 Long-Run Results

In this subsection, our focus shifts to the effects observed one year after the initial SMS interventions. A significant policy change took place in the winter of 2019–2020 in China, which banned the use of coal burning stoves and compelled all consumers to switch to electric heating. However, the mere prohibition of coal heating does not guarantee that households will automatically increase their usage of electric heating.

Conducting a formal t-test to compare the means of daily electric heating consumption in the control group between the pre-treatment period and the post-treatment winter period

[15]Note that our Social Comparison SMS intervention is specifically designed to test the effect of providing social comparison information rather than observational learning.

in 2019 yields a non-significant result, with a p-value of 0.40. To investigate whether our SMS interventions had a lasting effect, particularly in terms of household heterogeneity, we analyze households' electric heating consumption from November 2019 to March 2020 as the post-treatment period and estimate Equations (1) and (2).[16]

Table 5: Long-run Average Treatment Effects on Electric Heating

	Electricity Consumption for Heating			
	(1)	(2)	(3)	(4)
Cost SMS × Post	-1.691***	-1.689***	-1.689***	-1.688***
	(0.625)	(0.593)	(0.593)	(0.623)
Health SMS × Post	-0.205	-0.204	-0.203	-0.206
	(0.538)	(0.537)	(0.537)	(0.497)
Social Comparison SMS × Post	0.125	0.128	0.128	0.140
	(0.546)	(0.552)	(0.551)	(0.529)
Day fixed effects	Yes	Yes	Yes	Yes
Village fixed effects	Yes	Yes	Yes	Yes
Control variables	No	Yes	Yes	No
Household fixed effects	No	No	No	Yes
Obs.	6,970	6,970	6,970	6,970
Adjusted R^2	0.043	0.129	0.131	0.618

Note: Robust standard errors are reported in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 5 reports the long-run average effects of our SMS interventions. Overall, we find strong evidence of the lasting effects of the Cost SMS. In the year following the initial study, households in the Cost SMS group significantly lowered their electric heating consumption by 1.7 kWh relative to the control group. However, we did not find any statistically significant long-run treatment effects for the Health SMS and Social Comparison SMS campaigns. These results are in line with the short-run average effects reported in Table 3.

Table 6 presents the long-run heterogeneous treatment effects using regressions analogous to Equations (2) and (3). Panel A reports the long-run heterogeneous treatment effects of the Cost SMS. The results indicate that the negative impact of the Cost SMS campaign remains statistically significant after one year, particularly for households that did not overestimate costs or expressed concern about the expenses associated with heating during the initial stage of the study. This finding suggests that the salience effect of the Cost SMS intervention continues to influence cost-conscious households, leading them to exhibit hesitation in adopting electric heating.

In contrast to the findings in Table 4, we do not observe any long-run negative effects among

[16] Our data for the pre-treatment period contain daily electric heating consumption, while the data for November 2019–March 2020 are for monthly consumption. We first transform monthly electric heating to average daily level and then estimate Equation (1).

households with above-median income. However, for households with below-median income, the long-run effect remains significantly negative (with a p-value of 0.011). This indicates that the salience of the Cost SMS intervention is only temporary for relatively affluent households. Once electric heating becomes mandatory, those who have the financial means will readily adopt it.

Panel B of Table 6 presents the long-run heterogeneous treatment effects of the Health SMS intervention. It is expected that households who did not underestimate the health damage caused by coal heating and expressed concern about it during the initial stage of the study would be more receptive to electric heating. Upon receiving the Health SMS, these households would have developed a habit of using electric heating. Consequently, when coal heating is prohibited, it is likely that households in this group would adopt electric heating more consistently compared to their counterparts in the control group. However, our analysis reveals that, despite their initial receptiveness, the Health SMS intervention does not have a sustained impact on their electric heating behavior in the long run. The long-run effects are not significantly different between the two categories (Columns 1–4 of Panel B), indicating that the positive heterogeneous effects of the Health SMS intervention are only temporary. Furthermore, we observe that the negative effects of the Health SMS intervention persist for households with lower income levels and those without primary school education even after one year. Considering the findings in Table 4 and the limited likelihood that these households being able to afford electric heating, these results are expected.

Panel C of Table 6 shows that there is no significant long-run effect of the Social Comparison SMS campaign on the participants who were concerned about their neighbors' heating choices. This result is not surprising, as the use of electric heating had become compulsory by then, making comparison with others superfluous.

Taken together, the results from Tables 5 and 6 highlight the persistence of the negative effect of the Cost SMS, particularly for households that underestimated energy costs and expressed concerns about expenses. This suggests that cost considerations outweigh both health concerns and information regarding neighbors' heating preferences in influencing household behavior. On the other hand, the positive effects observed for the Health SMS and Social Comparison SMS campaigns observed in Table 4 appear to be mostly temporary.

Result 5: *The Cost SMS has a significant long-run effect, while the Health SMS and Social Comparison SMS do not show significant effects in the long-run.*

7 Conclusion

Using a randomized field experiment, we investigate the effects of three different types of information nudges aimed at promoting the use of electric heating. The interventions include a Cost SMS campaign, designed to address the overestimation of electricity expenses; a Health SMS campaign, aimed at addressing the underestimation of health damage associated with coal heating; and a Social Comparison SMS campaign, intended to inform households about the popularity of electric heating. These interventions serve to alleviate imperfect information, and ultimately encouraging greater adoption of electric heating. However, it is important to acknowledge that some households may perceive these interventions as paternalistic (Allcott,

Table 6: Long-run Heterogeneous Treatment Effects on Electric Heating

Panel A: Heterogeneous Treatment Effects of Cost SMS

	Overestimate electricity cost		Price Concern		Monthly income ⩾ RMB2,000	
	(Yes)	(No)	(Yes)	(No)	(Yes)	(No)
	(1)	(2)	(3)	(4)	(5)	(6)
Cost SMS×Post	-0.600	-7.354**	-2.524**	-0.881	-0.578	-3.982***
	(0.514)	(3.137)	(1.020)	(0.730)	(0.870)	(1.026)
Obs.	2,374	450	1,741	1,833	1,952	1,412
Adjusted R^2	0.607	0.603	0.615	0.686	0.607	0.693
Fixed effects: Day, Village, Individual household						
Difference [p-value]	6.754**	[0.034]	-1.643	[0.189]	3.404**	[0.011]

Panel B: Heterogeneous Treatment Effects of Health SMS

	Underestimate health damage		Health Concern		Monthly income ⩾ RMB2,000		Attended primary school	
	(Yes)	(No)	(Yes)	(No)	(Yes)	(No)	(Yes)	(No)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Health SMS×Post	-0.095	-0.473	-0.074	-0.440	1.068	-2.011***	0.138	-4.052**
	(0.627)	(0.701)	(0.739)	(0.625)	(0.727)	(0.681)	(0.519)	(1.993)
Obs.	3,006	1,082	1,981	2,107	2,284	1,714	3,638	360
Adjusted R^2	0.614	0.407	0.605	0.532	0.625	0.440	0.599	0.356
Fixed effects: Day, Village, Individual household								
Difference [p-value]	0.378	[0.689]	0.366	[0.702]	3.079***	[0.002]	4.19**	[0.043]

Panel C: Heterogeneous Treatment Effects of Social Comparison SMS

	Concerned about neighbours' heating choices	
	(Yes)	(No)
	(1)	(2)
Social Comparison SMS×Post	-0.955	0.198
	(1.815)	(0.568)
Obs.	360	3,034
Adjusted R^2	0.350	0.568
Fixed effects: Day, Village, Individual household		
Difference [p-value]	-1.152 [0.539]	

Note: The difference between the coefficients in each paired category (Panel A: Column 1 vs. 2, Column 3 vs. 4, and Column 5 vs. 6; Panel B: Column 1 vs. 2, Column 3 vs. 4, Column 5 vs. 6, and Column 7 vs. 8; Panel C: Column 1 vs. 2) are reported in the last row of each panel, and p-values for the differences are shown in brackets. Robust standard errors are reported in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

2016; Glaeser, 2005; Thaler and Sunstein, 2003). This perception may lead households to reciprocate by reducing, rather than increasing, their usage of electric heating.

We find that a significant proportion of households overestimate the cost of electricity and underestimate the potential health damage of coal heating. However, we find no significant effect of the Cost SMS on households with cost overestimation. Surprisingly, we find that, on average, the demand for electric heating decreased by 52% following the Cost SMS intervention. This effect can be attributed to the salience bias (Sims, 2003; Chetty et al., 2009; Finkelstein, 2009; Brown et al., 2010; Lacetera et al., 2012; Tiefenbeck et al., 2018). The Cost SMS intervention may have drawn the attention to the cost of electric energy, leading households to become more conscious of these expenses. Additionally, this finding aligns with the hypothesis that households may be averse to paternalistic interventions.

The Health SMS intervention yielded positive effects for households that accurately assessed the level of health damage associated with coal heating and considered health as a significant factor in their heating method choice. Specifically, these households experienced a respective increase of 55.8% and 25.6% in their electric heating consumption levels compared to the control group. Surprisingly, the Health SMS intervention did not effectively enhance electric heating levels among households that underestimated the health damage of coal heating. In fact, households who indicated a lack of concern regarding the health consequences of heating reduced their electric heating usage by 25.4% after receiving the Health SMS. This result is consistent with the possibility that this particular group of households may be motivated to maintain their beliefs, resisting paternalistic interventions, and consequently reciprocating by reducing their electric heating usage.

Our analysis reveals no significant overall effect of the Social Comparison SMS intervention. However, we do observe a significant positive effect for a subset of households that demonstrated a tendency to align their choices with those of their neighbors. Additionally, our findings indicate that the preference for heating methods is not correlated with present bias, suggesting that time preferences do not play a significant role in influencing households' heating preferences.

While information nudges may initially seem like a cost-effective approach to promote the adoption of electric heating, our field experiment demonstrates that their effectiveness is limited and can sometimes have unintended consequences due to the salience bias, motivated beliefs, or their aversion to paternalistic interventions. To design effective nudge interventions, it is crucial to consider the heterogeneous beliefs and motivations of households. This entails accurately targeting the interventions to specific groups that are more receptive to them while avoiding groups that may resist or counteract the interventions. Achieving this level of precision would require obtaining accurate information about the recipients prior to implementing the intervention. In doing so, we can improve the efficacy of nudge interventions and enhance their overall impact.

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Online Appendices

A Additional Results

We explored the dynamic process of the average treatment effect in the six-week post-treatment period by dividing the post-treatment period into six separate weeks and compared changes in electric heating in each of the post-treatment weeks to the changes in the pre-treatment period. Figure A1 graphs the evolution of the average treatment effects, and the dotted lines depict the corresponding 95 percent confidence intervals. In analogous to Equation (4), we also include household fixed effects, week fixed effects, and village fixed effects. Table A1 in the Appendix A reports the estimate coefficients of the respective treatments across the weeks. It can be seen that after receiving Cost SMS, households reduced electric heating immediately, and by the end of the heating season, the reduction remained at about 1.35 kWh per day compared to the control group, which is a 57 percent reduction (p-value$= 0.004$). A formal F-test for the equality of the coefficients of interactions "Cost SMS$\times$W$_0$" and "Cost SMS$\times$W$_5$" shows that the treatment effect in the first post-treatment week is statistically indistinguishable from that in the last post-treatment week (p-value$= 0.314$). The effect of Health SMS and Social Comparison SMS were both statistically and economically insignificant across the post-treatment weeks.

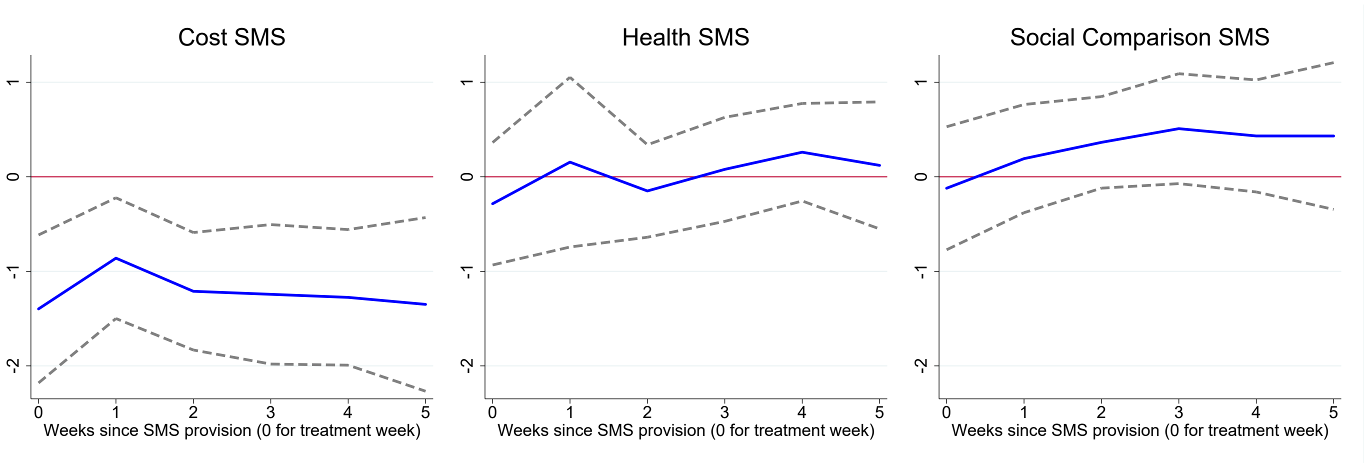

Figure A1: Average Treatment Effects Over Time

Notes: Estimates based on OLS regressions (Equation (4)). The three figures show the difference in electric heating consumption between the respective treatment and control groups by weeks since the SMS interventions. We controlled for village fixed effects, individual household fixed effects and week fixed effects. The dotted grey lines represent the ninety-fifth percent confidence interval.

Table A1: Average Treatment Effects on Electric Heating Over Time

	(1)	(2)	(3)	(4)	(5)	(6)
Cost SMS × Post1	-1.396***					
	(0.416)					
Health SMS × Post1	-0.286					
	(0.328)					
Social Comparison SMS × Post1	-0.115					
	(0.318)					
Cost SMS × Post2		-0.892**				
		(0.385)				
Health SMS × Post2		0.184				
		(0.498)				
Social Comparison SMS × Post2		0.190				
		(0.323)				
Cost SMS × Post3			-1.203***			
			(0.422)			
Health SMS × Post3			-0.175			
			(0.308)			
Social Comparison SMS × Post3			0.357			
			(0.286)			
Cost SMS × Post4				-1.248***		
				(0.468)		
Health SMS × Post4				0.078		
				(0.330)		
Social Comparison SMS × Post4				0.522		
				(0.329)		
Cost SMS × Post5					-1.275***	
					(0.459)	
Health SMS × Post5					0.260	
					(0.313)	
Social Comparison SMS × Post5					0.433	
					(0.333)	
Cost SMS × Post6						-1.345**
						(0.657)
Health SMS ×Post6						0.085
						(0.448)
Social Comparison SMS × Post6						0.445
						(0.472)
Day fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Village fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	7,898	7,316	7,557	7,659	7,666	6,948
Adjusted R^2	0.619	0.611	0.600	0.565	0.558	0.594

Notes: Post1, Post2, ..., and Post6 refers to the first, second, ..., and sixth post-treatment week. Robust standard errors are reported in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

B Survey Questionnaire

Meter number:

Welcome to participate in a survey on winter heating. You will receive a compensation for your participation. All your payment will be made through Alipay. This questionnaire consists of two parts.

Part 1: In each question, you have several options to choose from. The compensation for this part is 5 rmb. We will pay you after you complete the all the questions.

In Part 2, you have an opportunity to receive a prize of varying amount. The time and amount of the prize depend on your answer to each question of this part. **Therefore, please answer the questions carefully.**

Name: **Village:**

Phone number: **Alipay account:**

Part 1

1. How many electric heating equipment do you have at home, such as: electric heater, air conditioning, thermal oil heater?

- ____________
- None

2. What is the maximum kilowatt hour of them if you have electric heating equipment at home?

- _____________kilowatt hour
- I don't know.

3. How often do you use the electric heating equipment?
□ Rarely □ Every day □ Not used

4. If you do not have an electric heating equipment at home, what is reason? (Select all that apply)

- The electric heating equipment itself is too expensive
- The electricity bill is too expensive
- Used to coal heating
- Not sure how long the government subsidy can last

5. How many hours did you use the electric heating equipment yesterday?

- ____________ hour
- Did not use

6. How do you feel at night?

□Very cold □Tolerable □Just right □Warm □Hot

7. What is the electricity price per kilowatt hour?

□ 0.56 rmb/kwh □0.44 rmb/kwh □0.41 rmb/kwh □I don't know.

8. In general, what is your monthly electricity bill in winter?

__________________ rmb

9. In general, what is your monthly cost for coal heating in winter?

__________________ rmb

10. How much do you estimate for your electricity bill for yesterday？

__________________ rmb

11. How much more expensive of electric heating do you think compared to coal heating (in terms of percentage)?

______________________%

12. What is the size of your house? ________________square meter

13. Normally, how many people at home? _________________

14. What is the monthly income for your whole family？

- Below 1000 rmb
- 1000-2000 rmb（2000 rmb not included）
- 2000-3000 rmb（3000 rmb not included）
- 3000-4000 rmb（4000 rmb not included）
- 4000-5000 rmb（5000 rmb not included）
- 5000-6000 rmb（6000 rmb not included）
- Above 6000 rmb

15. What is your highest education level？

□No education attainment □Primary school □Middle school □High school □Technical school □College □Master and above

16. How old are you？ ____________

17. How do you think of your health condition compare to your peers?

□Very good □Good □Neither better nor worse □Bad □Very bad □I don't know

18. How do you think of your health condition compare to last year?

□Better □The same □Worse

19. Does anyone of your family have one of the following symptoms in the past year？（Please select all that apply）

- Asthma, pneumonia, lung tumors and other respiratory diseases
- Stroke, or atherosclerosis
- Heart disease
- Esophageal tumors
- Bowen dermatitis, precancerous dermatitis
- None
- I don't know

20. How much medical expenses in total did you pay for the treatment of the above diseases in the past year? ____________rmb

21. Which gender do you have?

□Male □Female

22. If you can choose, which of the following heating methods do you prefer?

□Burning coal □ Electric heating

23. On average, who have a longer life expectancy: people in the north or people in the south?

□ No significant difference

□ People in the south live longer

□ People in the north live longer

24. Scientific evidence shows that air pollution in the north is much higher than in that in the south due winter heating by burning coal. What do you think of the impact of the air pollution on the average life expectancy of people in the north and the south?

□ No impact

□ On average, people’s life expectancy in the north is 0.5 year shorter than their counterpart in the south.

□ On average, people’s life expectancy in the north is 1 year shorter than their counterpart in the south.

□ On average, people’s life expectancy in the north is 3 years shorter than their counterpart in the south.

□ On average, people’s life expectancy in the north is 5 years shorter than their counterpart in the south.

25. Burning coal will cause air pollution. Which of the following factors did you consider the most if you were allowed to choose heating methods (please select that all apply)?

□ Price □ Health □ Environment

□ Others' decision. If others use coal heating, I will follow.

Part 2

There are two groups of questions. Each group has six questions, and each question has a number. In each question, there are two options. Option A: a smaller and sooner prize. Option B: a large and later prize.

Please make your choice for each question. After you have completed all the questions, we will randomly select a number from 1 to 120 for you. If your selected number is between 1 and 12, you will receive a prize. The selected number corresponds to the question number, and you will be paid according to you chosen payment in that questoin. Please think of each decision carefully.

If you are a winner, we will inform you through text message, and transfer your payment through Alipay according to your chosen payment.

Group 1

(1) A：Receive 35 rmb today -------- B：receive 40 rmb in one month

(2) A：Receive 30 rmb today -------- B：receive 40 rmb in one month

(3) A：Receive 25 rmb today -------- B：receive 40 rmb in one month

(4) A：Receive 20 rmb today -------- B：receive 40 rmb in one month

(5) A：Receive 15 rmb today -------- B：receive 40 rmb in one month

(6) A：Receive 10 rmb today -------- B：receive 40 rmb in one month

Group 2

(7) A：Receive 35 rmb in six months -------- B：receive 40 rmb in seven months

(8) A：Receive 30 rmb in six months -------- B：receive 40 rmb in seven months

(9) A：Receive 25 rmb in six months -------- B：receive 40 rmb in seven months

(10) A：Receive 20 rmb in six months -------- B：receive 40 rmb in seven months

(11) A：Receive 15 rmb in six months -------- B：receive 40 rmb in seven months

(12) A：Receive 10 rmb in six months -------- B：receive 40 rmb in seven months

Thank you very much for completing our survey! Please return the questionnaire to our staff.