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FUELING CHANGE: IMPACT OF MASS MEDIA ON CLEAN COOKING FUEL ADOPTION IN RURAL INDIA

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Abstract

Our paper analyzes the causal impact of access to mass media on the adoption of clean cooking fuel in rural India. Using the 78th round of the National Sample Survey of India, we find that overall access to mass media increases the probability of using clean cooking fuel by 32 percentage points and reduces the probability of using dirty cooking fuel by 35 percentage points. To test for causality, we use an instrumental variable technique with two instruments. Our first instrument is the States/UTs-wise circulation of publications per capita, and our second instrument is the States/UTs-wise number of push SMSs sent per capita through the Government of India's Mobile Seva platform. Given the recent drive by the government to disseminate policy-related information digitally, we isolate the impact of digital mass media on the adoption of clean cooking fuel and find that digital mass media positively and significantly impacts adoption of clean cooking fuel. However, this impact is considerably weaker than the unconditional impact of mass media access. This suggests that the adoption of clean cooking fuel is still mostly driven by traditional mass media channels rather than digital ones.

Keywords: mass media, clean fuel, digital, rural, India

JEL Classification: C36, I18, O13, Q50

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1. INTRODUCTION

The lack of access to clean energy for cooking has become a global concern. Households largely rely on traditional fuels for cooking, which results in detrimental long-term health impacts. This phenomenon largely exists across households in the developing world. Using traditional sources of cooking fuel such as biomass, firewood, crop waste, and charcoal leads to household air pollution (HAP), leading to diseases of the lungs and the heart such as ischemic heart disease and lung cancer. As of 2022, almost 30% of the global population (2.4 billion) still rely on traditional cooking methods that cause high levels of HAP. Out of the 2.4 billion, 1.2 billion (50%) are from the Asian region, where 55% of the population do not have access to clean fuel (IEA 2023a). Another estimate by the International Energy Association (IEA) states that the **lack of clean energy for cooking contributes to 3.7 million premature deaths annually, with women and children being most at risk (IEA 2023b)**. The World Health Organization estimated that—HAP—was responsible for an estimated 3.2 million deaths per year in 2020, including over 237,000 deaths of children under the age of five (IEA et al. 2022). Most of the population affected by HAP live in low- and middle-income countries (WHO 2023).

The barriers to the adoption of clean fuel for cooking can be classified into three broad categories, namely accessibility, affordability, and awareness. In rural areas, the ease of collection of firewood and crop waste defines the energy use patterns in these households. Thus, households in rural areas tend to use crop waste and firewood as the primary energy source. Furthermore, income also plays a crucial role in deciding on the source of energy for fuel. The energy ladder hypothesis states that there is a hierarchical relationship between households' rise in economic status and the fuel type(s) used for cooking and heating (Hosier and Dowd 1987; Kroon et al. 2013). Extant research shows that household demographic factors such as income and education have a major effect on the choice of residential energy fuel (Baiyegunhi and Hassan 2014; Gregory and Stern 2014; Zhang and Hassen 2014; Nlom and Karimov 2015; Guta 2018; Onyeneke et al. 2019; Masrahi, Wang, and Abudiyah (2021); Zeru and Guta 2021; Waweru and Mose 2022). Furthermore, studies also show that accessibility and price play an important role in the adoption of clean fuel (Heltberg 2005; Hanna, Duflo, and Greenstone (2016); Jeuland et al. 2015; Rahut, Mottaleb, and Ali (2016); Gould and Urpelainen 2018). According to Toole, Klocker, and Head (2016) and Nansairo et al. (2011), the other important factors that affect the choice of household fuel are the cost of fuel, the cleanliness of fuel, energy efficiency, and convenience, to name a few. The effect of the size of the household on clean fuel adoption remains mixed. Özcan, Gülay, and Üçdoğruk (2013) and Pandey and Chaubal (2011) provide evidence that larger households prefer traditional fuel, while Baiyegunhi and Hassan (2014) show that larger households prefer cleaner fuel.

While household demographics play an important role in the choice of fuel adoption, the effect of external informational awareness cannot be understated. Jessoe and Rapson (2014) show that the energy consumption of households decreases when households are provided with information about energy price increases. Similarly, in India, exposure to newspaper and radio increased the probability of purifying drinking water (Jalan, Somanathan, and Chaudhuri 2009). Barnwal et al. (2017) show that when information about the level of arsenic in drinking water is provided to households, they switch the drinking water source. Dendup and Arimura (2019) show that households that have access to information are approximately 39% more likely to adopt clean cooking fuel. In a similar vein, Somanathan (2010) estimated that information awareness has a positive effect on household demand for certain environmental issues such as water quality and pesticides. Afridi, Debnath, and Somanathan (2019) conducted a randomized control trial to investigate whether creating awareness of the health hazards of indoor smoke from solid fuels leads to households mitigating the use of traditional fuels. The authors found that there was an increase in the adoption of LPG among households that were provided with combined information on health and financial awareness.

There are various channels through which information dissemination regarding the ill effects of using traditional fuel for cooking can occur. One of the most popular and most effective channels for information dissemination on a wide scale is mass media. Mass media is defined as comprising television, radio, and the internet. Mass media has been an instrument of change in socioeconomic development in various ways. Do, Figueroa, and Kincaid (2016) found that viewing educational television programs is positively correlated with health knowledge and a subsequent change in health behavior in Bangladesh. Using panel data on a set of states over five years, Jensen and Oster (2009) showed that the availability of television led to a decline in the overall domestic violence against women and improved women's autonomy. In India, the government spent INR1.5 billion (USD18 million) on a digital marketing strategy to ensure maximum awareness of public health schemes through campaigns on social media and other digital platforms (Dey 2015). Thus, apart from nondigital media like newspapers, the Indian government has actively been communicating its policies through a digital medium too.

Against this background, our research paper asks the following two research questions. First, does access to mass media increase the adoption of clean fuel in rural India? Second, how does this effect vary for digital mass media channels (internet, mobile phones). We limit our sample to rural households for two reasons. First, the proportion of adoption of clean fuel in India is 89% in urban India, but only 50% in rural India.[1] Therefore, raising the awareness of clean fuel adoption in the rural landscape becomes increasingly important. Second, most of the targeted intervention by the government is towards households in rural areas. These are households with relatively lower incomes that are in need of subsidies from the government as a support towards the adoption of LPG. We use household-level data from the 78th round of the National Sample Survey (NSS) of India, which was surveyed from January 2020 to August 2021. We use an instrumental variable approach to test for the causality of mass media access, with State/UTs-wise Total Average Circulation of Publications per capita and State/UTs-wise No. of Total Push SMS Sent per capita through Mobile Seva being our two instruments.

Our results indicate that overall access to mass media increases the probability of clean cooking fuel adoption by 32 percentage points in rural Indian households. We also find that access to mass media reduces the probability of the adoption of dirty cooking fuels by 35 percentage points. Further, our results show that access to digital mass media has a positive and significant impact on clean cooking fuel adoption; however, this impact is far weaker than the unconditional impact of access to mass media. Thus, our study implies that nondigital channels have a more substantial role in increasing clean fuel adoption than digital channels.

Our paper contributes to the two broad strands of existing literature. First, while extant literature has focused on the two key determinants of clean fuel adoption, which are affordability and accessibility (Kumar, Rao, and Reddy 2016), we extend this strand of literature by focusing on how awareness plays an important role in the adoption of clean fuel for cooking in India. Second, given the upsurge in the digitization of mass

1 Multiple Indicators Survey, 2020–2021 (NSS Round 78).

media channels (such as internet and mobile phones), we investigate the impact of the digital channels of mass media on the adoption of clean fuel. In doing so, we examine how access to digital infrastructure, including the internet and mobile phones, has played a crucial role in the adoption of clean fuel across rural households in India.

2. BACKGROUND AND CONCEPTUAL FRAMEWORK

To increase the access to clean cooking fuel in India, the federal government subsidizes the cost of LPG for low-income households in India. Starting in 2014, the government enacted several national-level policy changes, including reimbursement for household LPG purchases. The government initially marketed the use of LPG through subsidies. This would reduce the cost of LPG for households. However, this led to corruption and fraudulent practices in diverting subsidized LPG from legitimate consumers (Puzzolo and Pope 2017) to unintended beneficiaries. It was in 2015 that the direct transfer of subsidy benefits to consumers became mandatory. In the same year, the Government of India initiated the PAHAL program, the largest global direct beneficiary transfer scheme (DBT), with the objective of providing subsidies directly to the bank accounts of the intended beneficiaries. This program was launched with the objective of minimizing leakages in subsidies, with nearly 290 million households benefiting from the PAHAL scheme as of 2023.[2] Following the success of the PAHAL program, the Pradhan Mantri Ujjwala Yojana program (PMUY) was launched in 2016 in an effort to expand the reach of LPG access to households. The main objective of the scheme was to provide deposit-free LPG connections to women from poor households. Under this program, the beneficiaries are provided with a subsidy of USD20 and are provided with a first LPG refill and stove (hotplate), both free of charge, along with their deposit-free connection by the Oil Marketing Companies (OMCs). The PMUY program had an initial target of 50 million LPG connections in 2016, which increased to 80 million in 2019. Both these targets were successfully met. As of 2023, the total number of connections released under the PMUY program is 98 million.[3] The Ujjwal 2.0 program was launched in 2021, with the objective of increasing LPG access to an additional 16 million households. In addition, the program also provided a support of USD26 per connection, along with a refill and cooktop stove free of charge to the household. As of 2023, the number of connections reached under the Ujjwal 2.0 program crossed 18 million.[4] While cash transfer programs have been a popular mechanism through which governments nudge households to adopt a certain behavior, research has shown mixed evidence on the same. In a recent study on the impact of a transfer program on clean fuel adoption in India, Hanna and Oliva (2015) found that households shifted to using electricity rather than kerosene as their primary form of light; however, there was no effect on the adoption of LPG as a clean fuel.

Role of Information and Theory of Change

Information channels play a key role in the LPG access programs. One channel through which the government provides information to the key beneficiaries is mass media. Mass media plays a crucial role in policy dissemination with regard to public health. Mass media is defined as access to newspapers, radio, television, and/or the internet. Research evidence shows that information disseminated through mass media has led to positive health consequences globally. In Malawi, Meekers et al. (2017) found that radio communication campaigns had a significant effect on the use of

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2 My LPG.in.

3 PMUY: Home.

4 PMUY: Home.

contraceptives in Malawi. A study by Modugu, Panda, and Mind (2018) showed that education-focused entertainment shows led to a significant increase in the uptake of family planning methods in rural Bihar and Odisha.[5] In Ghana, the Campaign for Improved Cookstoves, dubbed “Obaatan Boafo” or “Mother’s Helper” locally, encouraged urban and peri-urban dwellers who depend on biomass and charcoal for cooking to switch to improved cookstoves that burn fuels more efficiently and effectively (Clean Cooking Alliance 2016). Similarly, in Uganda, the “cook and live” campaign, also known as “Fumbalive,” encouraged local consumers to adopt the use of improved cookstoves as a way of promoting energy-saving cooking practices. Thus, informational awareness by leveraging different mass media channels such as newspapers, television, the internet, or the radio has been successful in improving health standards across developing countries.

In the Indian context, information dissemination regarding the uptake of LPG as a cooking fuel had two objectives. First, the message had to convey that the use of traditional fuel like crop waste and charcoal has negative health consequences for individuals, households, and the environment. Second, the message had to promote the features of the various programs that were undertaken by the government in the most effective manner to maximize reach. The Mobile Seva program was launched by the Indian government as a part of the National Mobile Governance Initiative. Through this program, the Indian government sends push notifications and simple messaging services (SMSs) to intended beneficiaries on various governmental policies. The use of SMSs for health campaigns has been studied in a global context too. Johnson et al. (2017) showed that messages on the adoption of clean fuel had a positive impact on the uptake in Kenya. The *Give it Up* campaign was aimed at middle- and high-income class households transferring their subsidies to poor households. As of 2023, almost 11.3 million households had given up LPG subsidies.[6]

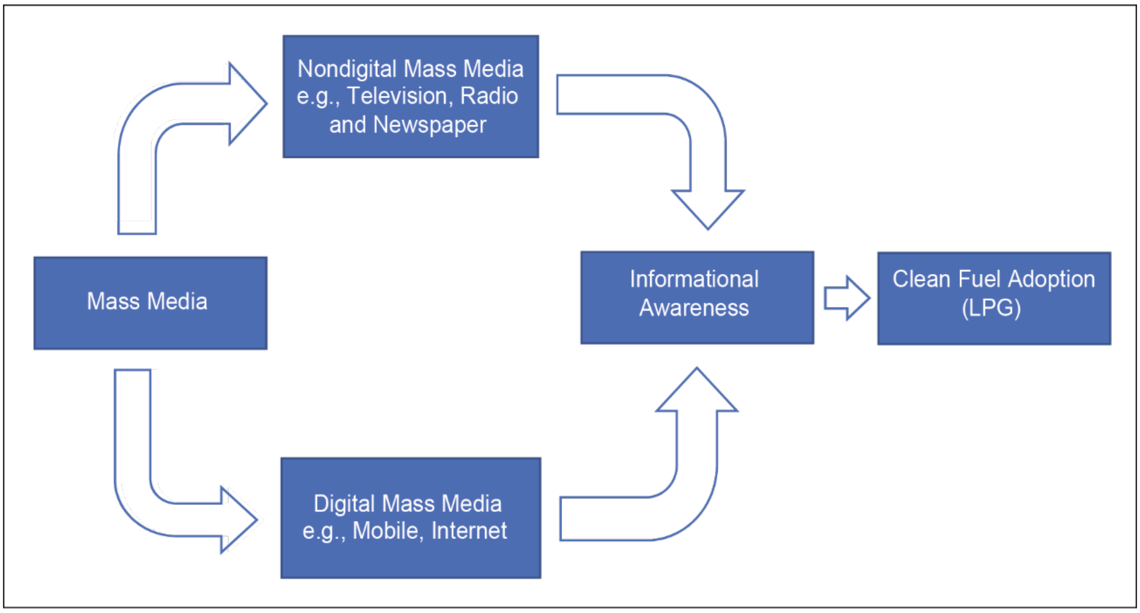
In Figure 1, we showcase the conceptual framework for our study. Informational awareness, which is defined as the access to mass media, has two components, namely nondigital and digital mass media.[7] In our study, we take the channels of mass media not defined under digital mass media as non-digital mass media. Thus, both these channels effect household decision to adopt clean fuel.

[5] In 2011, the Government of India approved the name change of the State of Orissa to Odisha. This document reflects this change. However, when reference is made to policies that predate the name change, the formal name Orissa is retained.

[6] Ministry of Petroleum and Natural Gas.

[7] According to the Ministry of Electronics and Information Technology of the Government of India, digital media is defined as digitized content that can be transmitted over the internet or computer networks and includes content received, stored, transmitted, edited, or processed by (a) an intermediary or (b) a publisher of news and current affairs content or a publisher of online curated content (The Information Technology [Intermediary Guidelines and Digital Media Ethics Code] Rules 2021).

Figure 1: Conceptual Framework of the Study



3. ESTIMATION STRATEGY

3.1 Measuring the Impact of Mass Media Access

Following utility theory, we assume that household "h" in state "s" selects cooking fuel from the available fuel basket when the utility of using clean fuel "c," i.e., U_{hs}^{c}, is greater than the utility from using dirty fuel "d," i.e., U_{hs}^{d}. The utility from cooking fuel adopted by households is not observed; only the fuel adopted by households is observed. Thus, our choice problem is described by a latent variable model, which is a measure of random utility:

$$Y_{hs}^{*} = X_{hs}\alpha + W_{s}\beta + M_{hs}\theta + \varepsilon_{hs}, \quad (1)$$

where $Y^{*} = U_{hs}^{c} - U_{hs}^{d}$, and $Y = 1$ if $Y^{*} > 0$ and 0 otherwise.

X_{hs} is a vector of exogenous household characteristics like the usual household monthly consumption expenditure, household landholding, household size, household religion, household social group, and the number of children and working females in the household. It also includes the gender, highest education level, and age of the household head. We also include information regarding the availability and accessibility of basic infrastructure to the household like bank accounts, electricity, drinking water, hand washing facilities, latrines, and proximity to an all-weather road. W_{s} is a vector of exogenous state-level characteristics that includes rural female literacy rates and rural unemployment rates to control for socioeconomic effects within the region in which the household lives.

As mentioned earlier, the Government of India has launched several schemes for incentivizing clean fuel adoption in India, especially among poor rural households. A major scheme in this context is the PMUY scheme.[8] To control for the possibility that

[8] The PMUY scheme was launched in May 2016 and reached its target in September 2019. The scheme further included a special package in March 2020 under the Pradhan Mantri Garib Kalyan Yojna

household clean fuel adoption can also be significantly impacted by government schemes operating in rural India, we include (within W_s) another variable that measures the average State/UTs-wise Per Capita Consumption of Liquefied Petroleum Gas (LPG) by PMUY beneficiaries between FY20 and FY22. For instance, at an all-India level, the average per capita consumption of LPG by PMUY beneficiaries (between FY20 and FY22) was 3.69 refills.

M_{hs} is a binary variable indicating household access to mass media and ε_{hs} is a normally distributed random error with zero mean and unit variance. In the MIS data, whether households are provided with information is not directly observed. Thus, we assume that households that have access to mass media are provided with information about the availability and accessibility of alternative fuels, the health benefits of clean fuel, the diseases caused by indoor pollution, and the availability of government support (through different schemes) to adopt clean fuels. The probability of a household using clean fuel is:

$$\text{Prob}\,[Y_{hs} = 1\,] = \text{Prob}\,[X_{hs}\alpha + W_s\beta + M_{hs}\theta + \varepsilon_{hs} > 0] = \phi[X_{hs}\alpha + W_s\beta + M_{hs}\theta], \quad (2)$$

where $\phi[]$ is the evaluation of the standard normal cumulative distribution function.

If M_{hs} were assumed to be an exogeneous variable, i.e., E ($\varepsilon_{hs}| M_{hs}$) = 0, then we could directly isolate the impact of mass media through Equation (1) using a standard univariate probit model. The quantitative impact of M_{hs} on clean fuel adoption would then be calculated as $\delta\ \text{Prob}(Y_{hs} = 1\,)/\delta\ M_{hs}$ for an average household.

However, the access to mass media in a particular household is not randomly assigned, and it is likely that unobserved factors that explain a household decision to adopt clean fuel for cooking may also be correlated with household access to mass media. For instance, it is possible that informal peer networks within rural Indian villages could be responsible for informing households about the multiple benefits of clean fuel or the government schemes focusing on its adoption. These informal peer networks could also be correlated to a household decision to use mass media, particularly newspapers. The presence of such unobservable factors could make the variable M_{hs} endogenous. Given that M_{hs} is a latent variable as well, we can estimate a model for its adoption as:

$$M^*_{hs} = X_{hs}\pi_1 + W_s\pi_2 + Z_s\pi_3 + \mu_{hs,} \quad (3)$$

where X_{hs} , W_s, and Z_s are vectors of exogeneous observables and μ_{hs} is a random error.

A household will adopt mass media if the net benefit of using it is positive. Thus, $M_{hs} = 1$ if $M^*_{hs} > 0$ and 0 otherwise. To allow for the possibility that the unobserved determinants of the household decision to use mass media and the unobserved determinants of the household decision to adopt clean fuel are correlated, we assume that ε_{hs} and μ_{hs} have a bivariate normal distribution, with E [ε_{hs}] = E [μ_{hs}] = 0, var [ε_{hs}] = var [μ_{hs}] = 1, and cov [$\varepsilon_{hs}, \mu_{hs}$] = ρ. As both decisions we model are dichotomous, there are four possible states of the world, i.e., Y_{hs} = 0 or 1 and M_{hs} = 0 or 1. Thus, the likelihood function corresponding to this set of events is a bivariate probit as in Heckman (1978). If the error terms ε_{hs} and μ_{hs} are correlated, then the outcomes are

(PMGKY). The PMGKY provided free LPG cylinders to PMUY beneficiaries for three months from April 2020. This was followed by the Ujjwala 2.0 scheme launched in September 2021 to succeed the PMUY scheme and provide an additional 10 million LPG connections to adult women of poor households (Ministry of Petroleum and Natural Gas, Government of India).

endogenously determined; a significance test of the correlation coefficient ρ is a test of endogeneity between mass media access and clean fuel adoption (Fabbri et al. 2004). This system is identified if at least one more exogenous variable is included in (3) that is not contained in (1). For our instrument Z_s, we use two variables, namely the State/UTs-wise Total Average Circulation of Publications per capita[9] and State/UTs-wise No. of Total Push SMS Sent per capita through Mobile Seva.[10] In the Appendix, we provide a detailed justification of the validity of our instruments.

The average partial effect (APE) of household access to mass media on the probability of a household choosing clean fuel is:

$$\text{Prob}\,[Y_{hs}=1\mid M_{hs}=1\,]-\text{Prob}[Y_{hs}=1\mid M_{hs}=0\,]=\phi[X_{hs}\alpha+W_s\beta+\theta] - \phi[X_{hs}\alpha+W_s\beta]. \tag{4}$$

3.2 Isolating the Impact of Digital Mass Media Access

An advantage within the MIS survey is that the information collected on household access to mass media includes multiple channels of mass media like the internet, newspapers, magazines, radio, television, etc. The inclusion of the internet as a potential channel allows us to isolate the impact of digital mass media on clean fuel adoption. To the best of our knowledge, no study to date has quantified this impact. This quantification becomes even more important for India for three reasons. First, there has been a massive increase in mobile phone adoption over the years. Smartphone penetration increased from 2.75% in 2010 to 66.2% in 2022.[11] Second, almost 63% of the population uses the internet in India, which is close to 600 million individuals.[12] Lastly, the government has been expanding the use of digital platforms, especially mobiles, to increasingly disseminate some of their services to households in India. For instance, Mobile Seva is an initiative that provides an integrated whole-of-government platform to all government departments and agencies in India for the delivery of public services to citizens and businesses over mobile devices using SMS, USSD, IVRS, CBS, LBS, and mobile applications installed on mobile phones.[13] Thus, determining the impact of digital mass media would aid policymakers in selecting the right channel through which information on clean fuel adoption can be disseminated more efficiently.

Even though the MIS data set collects information on digital and nondigital channels of mass media access, it doesn't isolate their impact. Interestingly, it also collects information on access to an active mobile phone[14] at an individual level as well as access to broadband[15] at a household level. To isolate the impact of digital mass media, we make the assumption that a household that has access to mass media,

[9] Total Average Circulation of Publications per capita is constructed by dividing the total of average daily, average weekly, average fortnightly, average monthly, average quarterly, and average annual publications in each State/UT in 2020–2021 by the total population in each State/UT during the same period.

[10] Total Push SMS Sent per capita is constructed by dividing the number of Push SMS sent in each State/UT (until June 2021) by the total population in each State/UT as of March 2021.

[11] Statista. Smartphone Penetration Rate in India from 2009 to 2023, with Estimates until 2040.

[12] World Bank. Data. Individuals Using the Internet (% of population) – India (accessed 27 July 2023).

[13] Mobile Seva.

[14] In the MIS survey, it was asked whether an individual (above the age of 15) had used any mobile telephone with an active sim card at least once during the last three months preceding the date of the survey.

[15] In the MIS survey, it was asked whether households had broadband access within their premises.

access to broadband, and whose head uses an active mobile phone will be able to access digital mass media. For estimating this impact of access to digital mass media on the probability of a household decision to adopt clean fuel, we modify (1) to:

$$Y_{hs}^{*} = X_{hs}\alpha + W_s\beta + M_{hs}\theta + I_{hs}\gamma + M_{hs}I_{hs}\varphi + v_{hs}, \quad (5)$$

where I_{hs} is an exogenous binary variable indicating household access to broadband and a household head's access to mobile. X_{hs}, M_{hs}, and W_s are the same variables as in (1) and v_{hs} is a normally distributed random error with zero mean and unit variance. The coefficient of the interaction term $M_{hs}I_{hs,}$ i.e., φ, isolates the impact of digital mass media on household clean fuel adoption.

Given the endogeneity of M_{hs}, we estimate a bivariate probit model using a similar technique to that explained in the previous subsection but via Equations (5) and (3). As pointed out in Wooldridge (2010: 596), we can estimate the correct estimates of our parameters in (5) by including the interaction term in the structural equation of bivariate probit and specifying M_{hs} as the only endogenous variable. In such a case, E [v_{hs}] = E [μ_{hs}] = 0, var [v_{hs}] = var [μ_{hs}] = 1, and cov [v_{hs}, μ_{hs}] = ρ. We can then calculate the APE of household access to digital mass media on the probability of household clean fuel adoption as:

$$\{\text{Prob}\,[Y_{hs} = 1 \mid M_{hs} = 1, I_{hs} = 1\,] - \text{Prob}\,[Y_{hs} = 1 \mid M_{hs} = 1, I_{hs} = 0\,]\} - \{\,\text{Prob}\,[Y_{hs} = 1 \mid M_{hs} = 0, I_{hs} = 1\,] - \text{Prob}\,[Y_{hs} = 1 \mid M_{hs} = 0, I_{hs} = 0\,]\}$$

$$=$$

$$\{\phi[X_{hs}\alpha + W_s\beta + \theta + \gamma + \varphi] - \phi[X_{hs}\alpha + W_s\beta + \theta]\} - \{\phi[X_{hs}\alpha + W_s\beta + \gamma] - \phi[X_{hs}\alpha + W_s\beta]\,\}. \quad (6)$$

To check the robustness of our results, we substitute I_{hs} with a new variable L_{hs} and estimate the same modeling procedure as explained above. L_{hs} is an exogenous binary variable that indicates household access to broadband, household head access to mobile, and household head attainment of a basic level of digital literacy.[16]

In these two subsections, only the adoption of clean cooking fuel is described. However, an adoption model for dirty cooking fuel is also estimated in our study, and the same discussion applies to that model as well. We assume that households that have access to mass media/digital mass media will also acquire information about the consequences of burning dirty fuel and this could also lead them to reduce their adoption of the same. Thus, this model for dirty cooking fuel adoption would serve as a robustness check for our clean cooking fuel model.

4. DATA AND VARIABLES

We use the unit level household data of the NSS 78th round: Multiple Indicator Survey (MIS), which was held between January 2020 and August 2021. The survey covers 276,409 households across all states and union territories of India, with it covering 164,529 households in the rural areas of the country. In addition, we use data sets exogenous to the MIS survey, which include data on certain state-level variables used in our model. The data on States/ UTs-wise female rural literacy and rural

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16 In the MIS database, information is collected on various digital literacy skills at an individual level. The most elementary of these skills is the individual ability to copy or move a file or folder. Hence, we assume that an individual that can to copy or move a file or folder has a basic level of digital literacy.

unemployment rate were obtained from the Periodic Labour Force Survey of 2020–2021 (Ministry of Statistics and Programme Implementation, National Statistics Office 2022). The data on State/UTs-wise Per Capita Consumption of Liquefied Petroleum Gas (LPG) by PMUY beneficiaries[17] and regarding State/UTs-wise No. of Total Push SMS Sent through Mobile Seva[18] were taken from two questions answered by the government in the upper house of the Indian parliament. The information on the State/UTs-wise Total Average Circulation of Publications was obtained from the 2020–2021 Press in India report, published by the Office of the Registrar of Newspapers for India (RNI).[19, 20] The data on the State/UTs-wise total population were obtained from the report of the technical group on population projections that was published by the National Commission on Population in July 2020 (National Commission on Population, Ministry of Health & Family Welfare 2020). We exclude the States/UTs of Tripura, Dadra, and Nagar Haveli, Daman and Diu, Lakshadweep, and Ladakh due to a lack of availability of data within these regions on certain state-level variables. Thus, our final data set for analysis contains a total 160,373 households distributed across rural India.

In the MIS survey, information is collected on the primary source of energy used for cooking within each household. The primary source of energy for cooking is defined as the source of energy that the household used for the majority of its time during cooking. The data for this variable were collected in terms of 13 categories as shown in Table 1. A disadvantage of eliciting fuel usage in this way is the inability to identify whether any other fuels could have been used by the households for a significant amount of time (but less than the majority). As Dendup and Arimura (2019) point out, this inability can mask the phenomenon of fuel stacking, which is very pertinent in developing countries.

Table 1: Distribution of Primary Cooking Fuel in Rural India

Primary Source of Cooking fuel	**Share of Rural Households** (%)
Firewood, chips, and crop residue	46.59
LPG	49.42
Other natural gas	0.16
Dung cake	3.04
Kerosene	0.06
Coke, coal	0.32
Gobar gas	0.09
Other biogas	0.01
Charcoal	0.02
Electricity (incl. generated by solar/wind power generators)	0.03
Solar cooker	0
Others	0.22
No cooking arrangement	0.03

Source: Author's computation of MIS data.

[17] Rajya Sabha Session – 256, Unstarred Question No. 2057.

[18] Rajya Sabha Session – 254, Unstarred Question No. 2001.

[19] Office of Registrar for Newspapers in India (RNI).

[20] Chapter 4 – Circulation of Publications. Press in India 2020–2021.

Nevertheless, as Table 1 evidently shows, the majority of households in rural India either use firewood or LPG as their primary source of energy for cooking. For our analysis, we categorize the households as clean cooking fuel users if their primary source of energy for cooking is either LPG, other natural gas, gobar gas, other biogas, electricity (incl. generated by solar/wind power generators), or solar cookers. Similarly, households are categorized as dirty cooking fuel users if their primary source of energy for cooking is either firewood, chips and crop residue, dung cake, kerosene, coking coal, or charcoal. The definitions and summary statistics of the variables used in our study are reported in Table 2. As Table 2 elucidates, there is nearly an equal division between using clean and dirty fuels for cooking in rural India.

Our primary explanatory variable is whether households have access to mass media. The MIS survey collects information from surveyed households on whether any of the household members have access to any form of mass media, such as the internet, newspapers, magazines, radio, television, etc. In rural India, 70.4% of households have overall access to mass media. Additionally, 79.1% of household heads have access to mobile, and 32.18% of households have access to broadband within their premises.

We also use several exogenous variables as controls in our analysis. These variables include controls for household demographics, household infrastructure, household access to external infrastructure, and regional socioeconomic characteristics (Gould and Urpelainen 2018; Dendup and Arimura 2019; Afridi, Debnath, and Somanathan. 2021; Thomas et al. 2022). Looking at demographic trends, we observe that the average household size in rural India is 4.5, with 12.6% of rural households having a female head. The level of education of household heads is low, with 36.3% of household heads not being literate, 23.1% being educated up to primary level, 12% and 6.6% being educated up to secondary and higher secondary levels, respectively, and only 5% of household heads having attained a university education or above. Further, 49.5% of households have exclusive access to drinking water and 68.7% have exclusive use of a latrine. Remarkably, the access of rural households to external infrastructure like electricity and roads is much more robust. Nearly 98.5% of rural households have electricity and 94.4% live near an all-weather road. The MIS data also report on the high level of financial penetration that has been achieved in rural India, with 98.5% of households having access to at least one bank/financial institution account. This information on power and financial infrastructure penetration in rural India is also similar to the information reported in the National Family Health Survey (NFHS)-5, which was conducted during a similar period. NFHS-5 (Ministry of Health and Family Welfare 2022) reported that 95% of rural households have electricity, and 96% of rural households have a bank or post office account. At a regional level, the average rural female literacy rate across states in India is 67.8%, and the average rural unemployment rate is 3.4% (Ministry of Health and Family Welfare 2022).

Table 2: Descriptive Statistics

Variable	Definition	Obs.	Mean	Std. Dev.	Min	Max
Dependent Variables						
HH access to clean fuel	1 if HH uses clean fuel for cooking	160,373	0.497	0.500	0	1
HH access to dirty fuel	1 if HH uses dirty fuel for cooking	160,373	0.500	0.500	0	1
Independent Variables						
HH access to mass media	1 if any of the HH members has access to any mass media (viz. internet, newspapers, magazines, radio, television, etc.)	160,373	0.704	0.457	0	1
HH usual monthly consumption expenditure	Log of HH usual monthly consumer expenditure (in INR)	160,373	8.876	0.568	4.828314	11.92393
HH access to at least one bank A/C	1 if HH has access to at least one bank A/C	160,373	0.985	0.122	0	1
Land	Land possessed by HH (in hectares)					
less than 0.005	1 if HH possessed less than 0.005 hectares	160,373	0.040	0.196	0	1
0.005 – 0.02	1 if HH possessed more than 0.005 hectares but less than 0.02 hectares	160,373	0.085	0.279	0	1
0.02 – 0.21	1 if HH possessed more than 0.02 hectares but less than 0.21 hectares	160,373	0.300	0.458	0	1
0.21 – 0.41	1 if HH possessed more than 0.21 hectares but less than 0.41 hectares	160,373	0.063	0.242	0	1
0.41 – 1.01	1 if HH possessed more than 0.41 hectares but less than 1.01 hectares	160,373	0.150	0.357	0	1
1.01 – 2.01	1 if HH possessed more than 1.01 hectares but less than 2.01 hectares	160,373	0.150	0.357	0	1
2.01 – 3.01	1 if HH possessed more than 2.01 hectares but less than 3.01 hectares	160,373	0.082	0.274	0	1
3.01 – 4.01	1 if HH possessed more than 3.01 hectares but less than 4.01 hectares	160,373	0.044	0.204	0	1
4.01 – 6.01	1 if HH possessed more than 4.01 hectares but less than 6.01 hectares	160,373	0.047	0.212	0	1
6.01 – 8.01	1 if HH possessed more than 6.01 hectares but less than 8.01 hectares	160,373	0.018	0.132	0	1
More than or equal to 8.01	1 if HH possessed more than 8.01 hectares	160,373	0.021	0.144	0	1
HH size	The number of members of a HH	160,373	4.496	2.092	1	29
Female HH head	1 if HH head is a female	160,373	0.123	0.329	0	1
No. of females in HH within LF	No. of females 15 and above in HH within the labor force	160,373	0.389	0.598	0	7
No. of children five and below in HH	No. of children five and below in HH	160,373	0.452	0.783	0	7
Highest education level of HH head						
Not literate	1 if HH head is not literate (i.e., not able to read or write a simple message with understanding in any language)	160,372	0.363	0.481	0	1
Literate with nonformal education	1 if HH head is literate with nonformal education (like NFEC, AEC, TLC, literate without any schooling, etc.)	160,372	0.013	0.112	0	1
Primary and below	1 if HH head is educated up to primary level or below	160,372	0.231	0.422	0	1
Upper primary/ middle	1 if HH head is educated up to upper primary level	160,372	0.156	0.363	0	1
Secondary	1 if HH head is educated up to secondary level (incl. diploma/certificate course)	160,372	0.120	0.325	0	1
Higher secondary	1 if HH head is educated up to higher secondary level (incl. diploma/certificate course)	160,372	0.066	0.248	0	1

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Table 2 *continued*

Variable	Definition	Obs.	Mean	Std. Dev.	Min	Max
Graduation and above	1 if HH head is educated up to graduate level or above (incl. diploma/certificate course)	160,372	0.050	0.219	0	1
Age of HH head	Age of HH head (in years)	160,373	48.280	13.840	0	114
Access of HH to an all-weather road	1 if an all-weather road is within a distance of 2 km from the place where the household lives	156,931	0.944	0.230	0	1
Religion of HH						
Hinduism	1 if HH head follows Hinduism	160,373	0.851	0.356	0	1
Islam	1 if HH head follows Islam	160,373	0.098	0.297	0	1
Christianity	1 if HH head follows Christianity	160,373	0.025	0.157	0	1
Sikhism	1 if HH head follows Sikhism	160,373	0.017	0.129	0	1
Jainism	1 if HH head follows Jainism	160,373	0.001	0.025	0	1
Buddhism	1 if HH head follows Buddhism	160,373	0.005	0.073	0	1
Zoroastrianism	1 if HH head follows Zoroastrianism	160,373	0.000	0.003	0	1
Others	1 if HH head follows any other religious category	160,373	0.003	0.058	0	1
Social Group of HH						
Scheduled tribe (ST)	1 if HH head belonged to scheduled tribe (ST) social group	160,373	0.120	0.325	0	1
Scheduled caste (SC)	1 if HH head belonged to scheduled caste (SC) social group	160,373	0.235	0.424	0	1
Other backward class (OBC)	1 if HH head belonged to other backward caste (OBC) social group	160,373	0.438	0.496	0	1
Others	1 if HH head belonged to any other social group	160,373	0.207	0.405	0	1
HH has exclusive access to drinking water	1 if HH has exclusive access to principal source of drinking water	160,373	0.495	0.500	0	1
HH access to latrine						
Exclusive use of HH	1 if HH has exclusive use of latrine	160,373	0.687	0.464	0	1
Common use of HH in the building	1 if HH has common use of latrine in the building	160,373	0.086	0.281	0	1
Public/community latrine without payment	1 if HH has use of a public/community latrine without payment	160,373	0.004	0.065	0	1
Public/community latrine with payment	1 if HH has use of a public/community latrine with payment	160,373	0.000	0.014	0	1
No access to latrine	1 if HH has no access to latrine	160,373	0.214	0.410	0	1
Others	1 if HH has other types of access to latrine	160,373	0.008	0.090	0	1
HH access to hand washing	1 if HH has hand washing facility available within the premises	160,373	0.983	0.128	0	1
HH access to electricity	1 if HH uses electricity as the primary source of energy for lighting	160,373	0.985	0.121	0	1
Rural female literacy in state of residence	State/UTs-wise rural female literacy for females aged 7 and above (%)	160,373	67.813	8.102	58	98
Rural unemployment rate in state of residence	State/UTs-wise rural unemployment rate	160,373	0.034	0.016	0.005	0.178
Statewise per capita consumption of LPG by PMUY beneficiaries	Log of average State/UTs-wise Per Capita Consumption of Liquefied Petroleum Gas (LPG) by Pradhan Mantri Ujjwala Yojana (PMUY) beneficiaries from 2019–2020 to 2021–2022.	160,373	1.324	0.186	0.6523252	2.002831
Newspaper circulation per capita	State/UTs-wise Total Average Circulation of Publications per capita in 2020–2021 (incl. daily, weekly, fortnightly, monthly, quarterly, annual, and others)	160,373	0.265	0.189	0.0377771	1.432793
Push SMS sent per capita	State/UTs-wise No. of Push SMS Sent per capita through Mobile Seva in 2021	160,373	12.898	13.870	0.0001768	61.49625

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Table 2 *continued*

Variable	Definition	Obs.	Mean	Std. Dev.	Min	Max
HH access to mass media# HH head access to mobile						
(0,0)	If HH has no access to mass media and HH head has no access to an active mobile phone					
(0,1)	If HH has no access to mass media and HH head has access to an active mobile phone	160373	0.202	0.401	0	1
(1,0)	If HH has access to mass media and HH head has no access to an active mobile phone	160373	0.115	0.318	0	1
(1,1)	If HH has access to mass media and HH head has access to an active mobile phone	160373	0.589	0.492	0	1
HH access to mass media# HH access to broadband						
(0,0)	If HH has no access to mass media and HH has no access to broadband within its premises					
(0,1)	If HH has no access to mass media and HH has access to broadband within its premises	160373	0.012	0.111	0	1
(1,0)	If HH has access to mass media and HH has no access to broadband within its premises	160373	0.395	0.489	0	1
(1,1)	If HH has access to mass media and HH has access to broadband within its premises	160373	0.309	0.462	0	1

Source: Author's computation of MIS data.

5. RESULTS AND ANALYSIS

5.1 Impact of Mass Media

We first interpret the results of subsection 3.1 for both clean and dirty cooking fuel. Assuming that our primary explanatory variable, i.e., access to mass media, is exogenous, we report the marginal effects of the univariate probit model in columns 1 and 2 within Table 3. As the table illustrates, the impact of household access to mass media is positive and significant for the adoption of clean cooking fuel with or without controls. Further, the impact of mass media access on dirty cooking fuel adoption is negative and significant.

To take into account the potential endogeneity in our primary expandatory variable, we estimate the bivariate probit model as discussed in subsection 3.1. The APEs of the bivariate probit model are reported in columns 3 and 4 within Table 3. Our results indicate that on average, household access to mass media increases the probability of clean cooking fuel adoption by 32 percentage points in a rural Indian household. In contrast, this access reduces the probability of dirty cooking fuel adoption by 35 percentage points.

Table 3: Regression Estimates from Univariate and Bivariate Probit Models

	Probit	Probit	Bivariate Probit	Bivariate Probit
	ME	ME	APE	APE
Clean Fuel	0.34***	0.20***	0.61***	0.32***
	(0.0037)	(0.0044)	(0.0104)	(0.025)
Dirty Fuel	–0.33***	–0.20***	–0.63***	–0.35***
	(0.0038)	(0.004)	(0.0084)	(0.023)
Controls	No	Yes	No	Yes
N	160,373	156,929	160,373	156,930

Robust standard errors in parentheses; ME: marginal effects; APE: average partial effects; * p < 0.1, ** p < 0.05, *** p < 0.01.

Table A5 provides comprehensive estimates of the impact of different controls on the probability of clean fuel adoption in rural Indian households. We find that the likelihood of adopting clean fuel is higher for households with smaller household sizes, higher consumption, and a more educated household head. Further, this likelihood is also high for households with a female head and those with better infrastructure access.

To check the robustness of our univariate probit, we also estimate a linear probability model (LPM). The OLS estimates of an LPM are considered reliable when the "predicted probability of the dependent variable is close to 0.5" (Wooldridge 2002). This reliability arises because the underlying conditional expectation function (CEF) is roughly linear in the middle. For checking the robustness of our bivariate probit model, we estimate a two-stage least squares (TSLS) model. As Angrist and Pischke (2008: 149–151) point out, the APE from a bivariate probit model is likely to be similar to TSLS estimates.

Table 4 presents our results for both the LPM and the TSLS model. As illustrated, in all cases access to mass media increases the probability of clean cooking fuel adoption and reduces the adoption of dirty cooking fuel in rural Indian households.

Table 4: Regression Estimates from LPM and TSLS Models

	LPM	LPM	TSLS	TSLS
	Coeff.	Coeff.	Coeff.	Coeff.
Clean Fuel	0.35***	0.21***	0.87***	0.50***
	(0.0041)	(0.0047)	(0.048)	(0.077)
Dirty Fuel	–0.34***	–0.21***	–0.92***	–0.56***
	(0.0042)	(0.0047)	(0.053)	(0.078)
Controls	No	Yes	No	Yes
N	160,373	156,930	160,373	156,930

Robust standard errors in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01.

5.2 Impact of Digital Mass Media

As discussed in subsection 3.2, we isolate the impact of digital mass media access on clean and dirty cooking fuel adoption. In Table 5, we report the marginal effects of both the univariate and bivariate probit models after incorporating the variable I_{hs}. The variable I_{hs} is an exogenous binary variable that indicates household access to broadband and the household head's access to mobile. The APEs of the bivariate probit model are calculated in the method as seen in Equation (6). On average, access to digital mass media increases the probability of adopting clean cooking fuel by 3 percentage points and reduces the use of dirty cooking fuel by the same amount. The unconditional probabilities of mass media access can be interpreted using the marginal effects estimated in Table A4 in the Appendix. These indicate that on average, access to mass media (not conditional on its digital channel) increases the probability of clean cooking fuel adoption by 33 percentage points and reduces the probability of dirty cooking fuel use by 36 percentage points. These unconditional results are very close to our estimates in the previous subsection, thus demonstrating the robustness of our results.

We now incorporate the variable digital literacy with I_{hs} and define L_{hs} as an exogenous binary variable that indicates household access to broadband, household head's access to mobile, and household head's attainment of a basic level of digital literacy. We find that the access to digital mass media increases the probability of household clean fuel adoption by 4 percentage points and reduces the probability of dirty fuel adoption by 5 percentage points. Similarly, the unconditional probabilities of mass media access increase the adoption of clean cooking fuel by 33 percentage points and reduce the adoption of dirty cooking fuel by 36 percentage points.

Thus, our results point to the fact that even though digital mass media has a positive and significant impact on clean cooking fuel adoption, this impact is far weaker than the unconditional impact of access to mass media. This implies that nondigital channels play a much more significant role in increasing clean fuel adoption than digital channels.

Table 5: Average Partial Effects of Univariate and Bivariate Probit Models with Digital Interaction Terms

		Probit	Probit	Bivariate Probit	Bivariate Probit
		APE	APE	APE	APE
Clean Fuel					
$(\mathbf{M_{hs}}, \mathbf{I_{hs}})$	(0,0)	0.25***	0.34***	0.1***	0.25***
		(0.0034)	(0.0041)	(0.0076)	(0.016)
	(0,1)	0.39***	0.38***	0.17***	0.27***
		(0.020)	(0.019)	(0.0076)	(0.025)
	(1,0)	0.55***	0.54***	0.66***	0.58***
		(0.0031)	(0.0029)	(0.0080)	(0.0080)
	(1,1)	0.68***	0.59***	0.77***	0.63***
		(0.0037)	(0.0041)	(0.0051)	(0.0087)
$(\mathbf{M_{hs}}, \boldsymbol{L_{hs}})$	(0,0)	0.25***	0.34***	0.09***	0.26***
		(0.0033)	(0.0040)	(0.0062)	(0.016)
	(0,1)	0.40***	0.38***	0.16***	0.28***
		(0.034)	(0.033)	(0.021)	(0.036)
	(1,0)	0.58***	0.55***	0.69***	0.59***
		(0.0027)	(0.0025)	(0.0058)	(0.0081)
	(1,1)	0.72***	0.60***	0.80***	0.65***
		(0.0058)	(0.0063)	(0.0051)	(0.010)

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Table 5 *continued*

		Probit	Probit	Bivariate Probit	Bivariate Probit
		APE	APE	APE	APE
Dirty Fuel					
$(\mathbf{M_{hs}}, \mathbf{I_{hs}})$	(0,0)	0.75***	0.66***	0.91***	0.77***
		(0.0035)	(0.0040)	(0.0061)	(0.014)
	(0,1)	0.61***	0.62***	0.86***	0.75***
		(0.02)	(0.019)	(0.015)	(0.023)
	(1,0)	0.45***	0.46***	0.33***	0.41***
		(0.0032)	(0.0029)	(0.0070)	(0.0076)
	(1,1)	0.31***	0.41***	0.23***	0.36***
		(0.0037)	(0.0040)	(0.0041)	(0.0082)
$(\mathbf{M_{hs}}, \boldsymbol{L}_{\mathbf{hs}})$	(0,0)	0.74***	0.65***	0.91***	0.76***
		(0.0035)	(0.0039)	(0.0049)	(0.015)
	(0,1)	0.60***	0.62***	0.86***	0.75***
		(0.034)	(0.033)	(0.018)	(0.033)
	(1,0)	0.42***	0.45***	0.30***	0.40***
		(0.0027)	(0.0025)	(0.0048)	(0.0076)
	(1,1)	0.27***	0.39***	0.20***	0.34***
		(0.0058)	(0.0063)	(0.0045)	(0.0097)
Controls		No	Yes	No	Yes
N		160,373	156,929	160,373	156,930

Robust standard errors in parentheses; APE: average partial effects; * p < 0.1, ** p < 0.05, *** p < 0.01.

6. CONCLUSION AND POLICY IMPLICATIONS

The use of clean fuel has multiple benefits, not only at the household level but also at the environmental level. The use of traditional (dirty) fuel has adverse impacts on the health of the individuals in the household and also leads to environmental degradation. However, cleaner sources of fuel, such as LPG, are costly and therefore not adopted by many. Governments provide cash transfer programs and subsidies to reduce the cost of clean fuel for low-income households. However, the barrier to affordability is not enough to scale up the adoption of clean fuel. It is also equally and increasingly important to communicate effectively the ill effects of using traditional fuel, as well as the availability of subsidy programs that governments are offering towards achieving this step. Hence, designing effective communication channels becomes critical in the implementation of the programs.

In this paper, we examine the effect of access to mass media on clean fuel adoption in rural India. We show that there is a significant and positive causal impact of access to mass media on clean fuel adoption. Furthermore, digital mass media has a positive and significant causal impact on the adoption of clean fuel across rural households; however, this impact is relatively weaker than that of nondigital mass media channels. Both these results point to the fact that mass media plays a crucial role in the adoption of clean fuel. Hence, governments should leverage on the use of mass media in channelizing important information that could lead to a higher adoption rate across households in India.

Our paper has important policy implications for various stakeholders in the ecosystem. First, governments should engage more effectively with different media channels to disseminate important program-level information. Given the dissemination of digital communication media, including social media, the internet, and mobile phones, governments can leverage on this infrastructure for effective communication. Second, to promote the use of LPG among rural households in India, the government should work in close collaboration with oil marketing companies (OMCs) to organize public events for the distribution of connections and public awareness. The government has set up LPG Panchayats with the main objective of educating women about the benefits of using LPG instead of conventional fossil fuels. The first LPG Panchayat was set up in Uttar Pradesh in 2016. This was a good first step, and the government should continue to expand this offering to the entire country. Lastly, while mass media plays an important role in informational awareness, it is equally important to address the issue of the cost of adoption. The average price of LPG increased from USD7 in 2016–2017 to USD10 in 2021–2022. The continuous adoption of clean fuel also greatly depends on the refill price of LPG. Hence, governments should keep a price check so as to ensure that the three goals of affordability, accessibility, and awareness are all met simultaneously, leading to a much higher adoption of clean fuel across the country.

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APPENDIX

A1. Validity of Instrument

If our instruments are valid, then (i) it must be a determinant of the decision of a household to access mass media, i.e., they must be sufficiently correlated with the endogenous variable, but (ii) it must not be a determinant of the decision of a household to adopt clean cooking fuel, i.e., it must not be correlated with the error term ε_{hs}. Thus, to showcase the validity of our instruments, we divide this section into two parts: one showing their relevance and the other their exogeneity.

A1.1 Relevance of Instrument

Our first instrument is the States/UTs-wise Total Average Circulation of Publications per capita for the year 2020–2021. While the RNI publishes State/UT-wise circulation data in great detail, it doesn't bifurcate it into rural and urban cohorts. To make sure that our data aren't biased towards urban cohorts of a particular State/UT, we look at the individual readership statistics that are published quarterly (until Q4 of 2019) in the Indian Readership Survey (IRS) (2019) conducted by the Media Research Users Council India. According to the latest available IRS statistics (Q4 2019), nearly 32% of all rural individuals (above the age of 12) had read newspapers or magazines in the month preceding the date when the IRS was conducted. Overall, 50.5% of the total circulation of publications in India were in rural areas. In order to confirm that no urban bias exists statistically, we estimate a simple ordinary least squares (OLS) model:

$$Circulation_s = X_s\alpha + Urbanization_s\beta + w_{hs.} \tag{7}$$

In (7), $Circulation_s$ is the Total Average Circulation of Publications per capita in State/UT "s", X_s is a vector of state-level controls that include the log of NSDP per capita,[1] availability of power per capita,[2] sex ratio at birth (Ministry of Health and Family Welfare 2022) and literacy rate (Ministry of Statistics and Programme Implementation, National Statistical Office 2022) (above the age of 7). We further include two more variables as controls, i.e., State/UT wise number of multi system operators (MSOs) per capita[3] and State/UT wise number of internet subscribers per 100 people (Telecom Regulatory Authority of India 2021). The inclusion of these two variables is in accordance with the IRS, which reports that 76% and 41% of all individuals in India (above the age of 12) had access to television or the internet, respectively, making these two channels significant substitutes for newspapers and other written publications. $Urbanization_s$ refers to the share of urban population in each State/UT in India in 2020–2021. As Table A1 illustrates, the coefficient β is statistically insignificant, i.e., urbanization of a State/UT has no impact on the newspaper circulation per capita in a State/UT.

[1] Reserve Bank of India. Handbook of Statistics on Indian States. https://m.rbi.org.in/scripts/AnnualPublications.aspx?head=Handbook+of+Statistics+on+Indian+States.

[2] Reserve Bank of India. Handbook of Statistics on Indian States. https://m.rbi.org.in/scripts/AnnualPublications.aspx?head=Handbook+of+Statistics+on+Indian+States.

[3] This variable is constructed by dividing the number of MSOs in each State/UT (from State/UT wise MSO 2021) by the population in each State/UT during the same period. An MSO receives the signals of different television channels, combines the same, and transmits this combined feed to multiple local cable operators.

Table A1: OLS Estimates of Determinants of State/UT-wise Total Average Circulation of Publications Per Capita

	State/UT-wise Total Average Circulation of Publications per capita
Urbanization	.725
	(.426)
Log of NSDP per capita	.012
	(.183)
Availability of power per capita	0
	(0)
Sex ratio at birth	.003
	(.002)
Literacy rate	–.016*
	(.008)
State/UT-wise number of MSOs per capita	–.001
	(.001)
State/UT-wise number of internet subscribers per 100 people	.002**
	(.001)
_cons	–2.222
	(3.286)
N	30
R-squared	.498
VIF	2.18

Robust standard errors are in parentheses; *** p < .01, ** p < .05, * p < .1.

To further check the relevance of this instrument statistically, we observe its coefficient, i.e., π_3 in Equation (3) from our bivariate probit estimates (in the online appendix). As the regression tables showcase, the coefficient of State/UT-wise Total Average Circulation of Publications per capita is positive and significant.

Our second instrument is the State/UT-wise No. of Total Push SMS Sent per capita through Mobile Seva until June 2021. While Mobile Seva is used to disseminate several government services through individually owned mobile devices, we are particularly interested in the role of the SMS Gateway component, which supports both push- and pull-based messaging services. According to the government, push services can be a significant channel through which common informational services can be disseminated to citizens as a group.[4] These services have become even more noteworthy for mass media dissemination due to the wide penetration of mobile phones in both rural and urban India. According to the MIS survey, 79% of rural household heads and 90% of urban household heads have access to an active mobile phone in our data set, signifying the utility of Mobile Seva. Even though the push SMS services through Mobile Seva are undertaken for the entirety of India, the government emphasizes the importance of this service in rural India given the dearth of mass media channels available. Thus, to ensure that our instrument isn't biased towards urban cohorts of each State/UT, we estimate a similar model to that in (7) with State/UTs-wise No. of Total Push SMS Sent per capita as the new dependent variable. We include the same state-level controls as in (7), except we remove the controls for television and internet adoption and include a control that measures the State/UT-wise wireless teledensity.[5]

[4] Mobile Seva.

[5] Wireless teledensity is defined as the number of mobile phone subscribers per 100 inhabitants within a geographical area. We collected the data on State/UT-wise wireless teledensity in 2020–2021 from

Table A2: OLS Estimates of Determinants of State/UT-wise No. of Total Push SMS Sent Per Capita

	State/UT-wise No. of Total Push SMS Sent per capita
Urbanization	14.708
	(23.673)
Log of NSDP per capita	–7.243
	(10.178)
Availability of power per capita	–.006
	(.007)
Sex ratio at birth	–.107*
	(.061)
Literacy rate	–.529
	(.449)
State/UT-wise wireless teledensity	.235
	(.21)
_cons	217.194**
	(95.995)
N	31
R-squared	.244
VIF	3.06

Robust standard errors are in parentheses; *** p < .01, ** p < .05, * p < .1.

As Table A2 illustrates, more urbanized States/UTs don't necessarily have more push SMS sent per capita. Further, the coefficient of our instrument State/UT-wise No. of Total Push SMS Sent per capita in Equation (3) is positive and statistically significant, thus indicating its relevance for rural household mass media access.

Finally, to check the strength of our instruments, we utilize the TSLS model estimated in our study. Staiger and Stock (1997) suggested a rule of thumb that, in the case of a single endogenous regressor, instruments are deemed weak if the first-stage F statistic (of a TSLS model) is less than 10 (for any number of excluded instruments). This suggestion was based on the relative bias of TSLS. This thumb rule of Staiger and Stock (1997) is approximately a 5% significance test that the worst-case relative bias is approximately 10% or less. As Stock and Yogo (2005) point out, these critical values are satisfactory for a model with two excluded instruments or less. They also suggest another first-stage F statistic value that controls for size distortion. In this case, the F statistic value (for a model with one endogenous regressor and two excluded instruments) to have an expected maximal size of not more than 10% with a statistical significance of 5% is at least 19.93. In our model, the two excluded instruments have a first-stage F statistic value of 110.061.

A1.2 Exogeneity of Instrument

Theoretically, a big challenge to the exogeneity of our instruments arises if socioeconomic factors within a State/UT that impact the household decision to adopt clean/dirty cooking fuels also impact our instruments. In the case of both our instruments, these factors include the demand for information and knowledge within a particular State/UT or the income of the individuals in a state to afford different channels of information. As Tables 6 and 7 elucidate, State/UT per capita income

Telecom Regulatory Authority of India. Performance Indicators Reports. https://www.trai.gov.in/release-publication/reports/performance-indicators-reports.

(a proxy of individuals' ability to afford) is not a significant factor in determining either the circulation of publications or the dissemination of Push SMS. Similarly, the States/UTs literacy levels (proxying the demand for information and knowledge) is weakly significant with circulation of publications (with point estimate close to zero) and not significant for the dissemination of Push SMS.

We further test the exogeneity restrictions by utilizing the TSLS model we estimated earlier. We use Wooldridge's (1995) score test of overidentifying restrictions to test the exogeneity of our instruments. This test is identical to Sargan's (1958) statistic under the assumption of i.i.d. In this case, the null hypothesis tests two things: (a) whether the instruments are uncorrelated with the error term, and (b) whether the model is misspecified and that one or more of the excluded exogenous variables should in fact be included in the structural equation. Thus, a significant test statistic could represent either an invalid instrument or an incorrectly specified structural equation. As Table A3 illustrates, our null hypothesis is accepted, indicating that our instruments are exogeneous.

Table A3: Results of Wooldridge Robust Score Test of Overidentifying Restrictions

Chi-Square Statistic Value	P
1.04	0.3071

A2. Other Tables

Table A4: Unconditional Marginal Effects of M_{hs}, I_{hs}, and L_{hs}

			Probit	Probit	Bivariate Probit	Bivariate Probit
			ME	ME	ME	ME
Clean Fuel						
Model with I_{hs}	M_{hs}	0	0.29***	0.35***	0.12***	0.26***
			(0.0061)	(0.0064)	(0.0098)	(0.017)
		1	0.59***	0.55***	0.69***	0.59***
			(0.0025)	(0.0023)	(0.007)	(0.0079)
	I_{hs}	0	0.46***	0.48***	0.49***	0.49***
			(0.0025)	(0.0023)	(0.0037)	(0.0025)
		1	0.60***	0.53***	0.59***	0.53***
			(0.0065)	(0.0058)	(0.0040)	(0.0052)
Model with L_{hs}	M_{hs}	0	0.27***	0.34***	0.1***	0.26***
			(0.005)	(0.0051)	(0.0070)	(0.017)
		1	0.59***	0.55***	0.70***	0.59***
			(0.0025)	(0.0024)	(0.0055)	(0.0081)
	L_{hs}	0	0.48***	0.49***	0.51***	0.49***
			(0.0021)	(0.0019)	(0.0026)	(0.0021)
		1	0.63***	0.54***	0.61***	0.54***
			(0.011)	(0.0099)	(0.0063)	(0.0089)

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Table A4 *continued*

			Probit	Probit	Bivariate Probit	Bivariate Probit
			ME	ME	ME	ME
Dirty Fuel						
Model with I_{hs}	M_{hs}	0	0.71***	0.63***	0.90***	0.76***
			(0.0061)	(0.0063)	(0.0081)	(0.015)
		1	0.41***	0.45***	0.30***	0.40***
			(0.0025)	(0.0024)	(0.0059)	(0.0075)
	I_{hs}	0	0.54***	0.52***	0.50***	0.51***
			(0.0025)	(0.0023)	(0.0034)	(0.0024)
		1	0.40***	0.47***	0.41***	0.47***
			(0.0065)	(0.0058)	(0.0037)	(0.0050)
Model with L_{hs}	M_{hs}	0	0.73***	0.65***	0.91***	0.76***
			(0.0047)	(0.0051)	(0.0056)	(0.015)
		1	0.40***	0.45***	0.29***	0.40***
			(0.0025)	(0.0024)	(0.0045)	(0.0076)
	L_{hs}	0	0.52***	0.51***	0.48***	0.50***
			(0.0021)	(0.0020)	(0.0023)	(0.0021)
		1	0.37***	0.46***	0.39***	0.46***
			(0.011)	(0.0098)	(0.0057)	(0.0085)
Controls			No	Yes	No	Yes
N			160,373	156,929	160,373	156,930

Robust standard errors in parentheses; ME: marginal effects; * p < 0.1, ** p < 0.05, *** p < 0.01.

Table A5: Regression Estimates of Univariate and Bivariate Probit Models with Clean Cooking Fuel

	(1)	(2)	(3)		(4)	
	Probit	Probit	Bivariate Probit		Bivariate Probit	
	Clean Fuel	Clean Fuel	Clean Fuel	Mass Media	Clean Fuel	Mass Media
HH access to mass media	0.92***	0.63***	1.86***		0.96***	
	(0.012)	(0.015)	(0.048)		(0.077)	
HH usual monthly consumption expenditure		0.30***			0.23***	0.66***
		(0.016)			(0.021)	(0.019)
HH access to at least one bank A/C		0.17***			0.12**	0.45***
		(0.055)			(0.055)	(0.063)
Land possessed by HH (in hectares)						
less than 0.005		0			0	0
		(.)			(.)	(.)
0.005 – 0.02		–0.066			–0.072	0.096*
		(0.047)			(0.046)	(0.058)
0.02 – 0.21		–0.15***			–0.16***	0.14***
		(0.044)			(0.042)	(0.055)
0.21 – 0.41		–0.36***			–0.35***	–0.013
		(0.049)			(0.047)	(0.058)
0.41 – 1.01		–0.39***			–0.38***	–0.026
		(0.046)			(0.044)	(0.056)
1.01 – 2.01		–0.33***			–0.33***	0.080
		(0.046)			(0.044)	(0.056)
2.01 – 3.01		–0.27***			–0.29***	0.24***
		(0.048)			(0.046)	(0.059)

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Table A5 *continued*

	(1)	(2)	(3)		(4)	
	Probit	Probit	Bivariate Probit		Bivariate Probit	
	Clean Fuel	Clean Fuel	Clean Fuel	Mass Media	Clean Fuel	Mass Media
3.01 – 4.01		–0.20***			–0.23***	0.36***
		(0.051)			(0.050)	(0.064)
4.01 – 6.01		–0.16***			–0.20***	0.49***
		(0.051)			(0.050)	(0.064)
6.01 – 8.01		–0.14**			–0.17***	0.41***
		(0.063)			(0.063)	(0.079)
More than or equal to 8.01		–0.21***			–0.23***	0.23***
		(0.058)			(0.056)	(0.073)
HH size		–0.086***			–0.082***	–0.021***
		(0.0046)			(0.0046)	(0.0054)
Female HH head		0.16***			0.15***	0.039*
		(0.018)			(0.018)	(0.020)
No. of females in HH within LF		–0.0082			–0.023**	0.15***
		(0.010)			(0.011)	(0.012)
No. of children five and below in HH		–0.010			–0.0026	–0.073***
		(0.0091)			(0.0093)	(0.0096)
Highest education level of HH head						
Not literate		0			0	0
		(.)			(.)	(.)
Literate with nonformal education		0.0055			–0.044	0.50***
		(0.057)			(0.058)	(0.060)
Primary and below		0.053***			0.025	0.26***
		(0.016)			(0.017)	(0.017)
Upper primary/middle		0.097***			0.058***	0.40***
		(0.019)			(0.021)	(0.020)
Secondary		0.30***			0.25***	0.58***
		(0.021)			(0.024)	(0.025)
Higher secondary		0.41***			0.35***	0.69***
		(0.026)			(0.030)	(0.030)
Graduation and above		0.59***			0.52***	0.88***
		(0.031)			(0.035)	(0.039)
Age of HH head		0.0051***			0.0048***	0.0033***
		(0.00048)			(0.00049)	(0.00054)
Access of HH to an all-weather road		0.040*			0.032	0.089***
		(0.024)			(0.024)	(0.025)
Religion of HH						
Hinduism		0			0	0
		(.)			(.)	(.)
Islam		–0.18***			–0.15***	–0.26***
		(0.021)			(0.022)	(0.023)
Christianity		0.19***			0.19***	0.041
		(0.034)			(0.033)	(0.048)
Sikhism		–0.27***			–0.27***	–0.026
		(0.042)			(0.042)	(0.058)
Jainism		1.07***			1.04***	0.48
		(0.24)			(0.23)	(0.36)
Buddhism		0.24***			0.23***	0.089
		(0.071)			(0.072)	(0.078)
Zoroastrianism		0			6.37***	–6.92***
		(.)			(0.17)	(0.15)
Others		–0.29***			–0.26***	–0.20**
		(0.065)			(0.065)	(0.086)

continued on next page

Table A5 *continued*

	(1)	(2)	(3)		(4)	
	Probit	Probit	Bivariate Probit		Bivariate Probit	
	Clean Fuel	Clean Fuel	Clean Fuel	Mass Media	Clean Fuel	Mass Media
Social group of HH						
Scheduled tribe (ST)		0			0	0
		(.)			(.)	(.)
Scheduled caste (SC)		0.18***			0.16***	0.24***
		(0.022)			(0.022)	(0.023)
Other backward class (OBC)		0.43***			0.39***	0.35***
		(0.020)			(0.022)	(0.021)
Others		0.37***			0.34***	0.32***
		(0.022)			(0.024)	(0.025)
HH has exclusive access to drinking water		0.28***			0.27***	0.097***
		(0.012)			(0.013)	(0.014)
HH has access to latrine						
Exclusive use of HH		0			0	0
		(.)			(.)	(.)
Common use of HH in the building		–0.16***			–0.14***	–0.13***
		(0.022)			(0.022)	(0.025)
Public/community latrine without payment		0.15			0.16*	–0.12
		(0.094)			(0.091)	(0.094)
Public/community latrine with payment		0.20			0.24	–0.56*
		(0.42)			(0.42)	(0.33)
No access to latrine		–0.46***			–0.39***	–0.58***
		(0.015)			(0.024)	(0.015)
Others		–0.42***			–0.38***	–0.37***
		(0.063)			(0.064)	(0.057)
HH access to hand washing facility within premises		–0.035			–0.044	0.11**
		(0.048)			(0.047)	(0.045)
HH access to electricity		0.54***			0.41***	1.21***
		(0.063)			(0.070)	(0.059)
Statewise per capita consumption of LPG by PMUY beneficiaries		1.44***			1.42***	0.26***
		(0.036)			(0.038)	(0.037)
Rural female literacy in state of residence		–0.013***			–0.015***	0.036***
		(0.00082)			(0.00089)	(0.0011)
Rural unemployment rate in state of residence		–2.38***			–2.25***	–0.78
		(0.38)			(0.37)	(0.50)
Newspaper circulation per capita				0.13***		0.30***
				(0.028)		(0.037)
Push SMS sent per capita				0.0093***		0.013***
				(0.00040)		(0.00070)
_cons	–0.66***	–4.88***	–1.32***	0.39***	–4.13***	–10.7***
	(0.010)	(0.16)	(0.035)	(0.0100)	(0.24)	(0.19)
Pseudo R-Square	0.075	0.187				
Rho			–0.84***		–0.20***	
			(0.089)		(0.049)	
Controls	No	Yes	No	No	Yes	Yes
N	160,373	156,929	160,373	160,373	156,930	156,930

Robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.