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Adding fuel to fire? Social spillovers and spatial disparities in the adoption of LPG in India

Suchita Srinivasan* Stefano Carattini†

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Abstract

The Indian population is still heavily reliant on solid biomass as a cooking fuel, especially in the rural areas, despite its negative health implications. Liquefied petroleum gas (LPG) is a clean alternative, but its higher cost implies that its use is often limited to the richer, urban areas of the country. This paper investigates whether social spillover effects might play a role in a household's decision to use LPG, how these effects vary across different sub-populations, and whether they exacerbate or ameliorate existing spatial disparities in LPG use. Using data from the National Sample Survey (NSS) and the India Human Development Survey (IHDS), this paper provides multiples strands of evidence that taken jointly suggest that positive social spillovers are present, and they diverge in strength between rural and urban areas, and across states. Spillovers are also found to be stronger for households that are members of social networks where common preferences for food and/or fuel may be weak, than for households that do not belong to any network. Specifically, we find that membership in religious or social groups or in agricultural cooperatives is likely to lead to weaker social spillovers. Our results provide partial evidence on convergence in LPG use rates across subgroups of the Indian population, and have strong implications for policy-makers who could leverage lessons from social learning to encourage consumers to switch to cleaner sources of energy in developing countries.

Keywords: Clean cooking fuels; LPG; Technological adoption; Social learning; India

JEL Codes: D83; Q48; Q53; R12; R23; R29

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1 Introduction

The use of solid biomass as a cooking fuel is still rampant in the developing world, and is one of the main causes of indoor air pollution (WHO, 2016). Smoke generated from burning wood contains harmful pollutants such as carbon monoxide and particulate matter. Almost three billion people in the world still cook and heat their homes using open fires and stoves that burn biomass such as firewood, animal dung, crop waste and coal, and almost 4.3 million people die prematurely each year due to illnesses that are directly related to the inefficient use of solid fuels (WHO, 2016).[1] IHME (2013) estimates that 2.9 million deaths were caused by indoor air pollution in 2013 due to PM 2.5 (particulate matter with diameter less than or equal to 2.5 micrometers). Causes of death range from pneumonia, stroke, heart disease, chronic obstructive pulmonary disease, to lung cancer. Approximately 50% of premature deaths due to pneumonia among children under five are caused by soot that is inhaled due to indoor air pollution (WHO, 2016).[2]

In addition to health implications, the use of solid biomass also has implications for the global environment. Bond et al. (2007) estimate that cooking with traditional biomass accounts for almost 18% of greenhouse gas emissions. In addition, their use also degrades local forests and ecological systems. For instance, burning of firewood to produce charcoal has been found to expedite the degradation of land, including arable land (OECD/IEA, 2006). These environmental concerns are particularly pressing in light of India's commitments in the Paris Agreement, where it pledged to create a carbon sink of 2.5 to 3 billion tonnes of CO_2 equivalent by increasing forest and tree cover, and to reduce its energy emissions intensity by 30-35% in 2030, compared to 2005 levels (UNFCCC, 2015).

The adoption and sustained use of clean cooking fuels, and efficient cookstoves, re-

[1] Solid fuel use is still common in South Asia, Africa and Latin America: in India, for instance, according to WHO estimates, almost 81% of the rural population still use solid fuels for cooking, and 26% of the urban population still relied on their use in 2013 (WHO, 2016).

[2] The risk of exposure is particularly high amongst women and children, who mostly stay indoors, and spend considerable amounts of time near open fires.

mains one of the primary means of mitigating the risks of indoor air pollution in countries like India. Clean cooking alternatives, such as liquefied petroleum gas (LPG) have grown in popularity over time, but rather slowly. From its entry into the Indian market in the 1960's, LPG was better supplied to urban areas, where its use was thus more prevalent, while rural adoption rates lagged behind. The Indian government, in order to incentivise consumers to switch to LPG, subsidised the cooking fuel considerably, but these subsidies have also been mainly targeted to urban areas, which further contributed to a widening gap between rural and urban rates of adoption.[3]

The literature abounds on the role of socioeconomic factors in determining which households use clean cooking fuels in developing countries (Lewis and Pattanayak 2012 provide a thorough literature review). While it is clear that income and access to LPG have played a significant role in shaping the pattern of LPG adoption in India, in this paper, we examine whether social interactions, or "spillovers", could also affect a household's choice of cooking fuel, and thereby contribute to the wide variations observed in Indian LPG adoption.

In particular, the objective of this paper is to investigate whether social spillovers exist in the use of LPG in India, and if they do, how they vary across rural and urban areas, across states, and within pre-existing social networks. In addition, we identify the role that membership in specific networks play in determining the average LPG adoption rates in villages and in urban blocks. By explicitly controlling for factors found to be important for LPG adoption in the literature, and incorporating a rich set of socio-economic and demographic controls, our paper provides multiple strands of evidence on why social spillovers may act as a possible determinant of a household's decision to adopt LPG. We provide complementary evidence on the presence of positive social spillovers, i.e. a household is more likely to adopt LPG if other households residing in the same village or urban

[3] Despite significant reductions in subsidies over the years, as of 2016-17, there is still an LPG subsidy of Rs. 108.73 (approximately USD 2) per litre per cylinder (Planning and Analysis Cell, 2015). A 14.2 kilogram cylinder of LPG costed Rs 761.60 (approximately USD 12) averaged across major Indian cities, as of April 2017 (Planning and Analysis Cell, 2015).

block do so. We also find evidence that these effects are stronger for rural households, and that they are weaker in states that had high prior rates of LPG adoption.

Importantly, we find that level of LPG adoption is higher amongst households that belong to certain groups or associations such as women's groups and self-help groups, in which flows of information (on LPG and its associated benefits) are likely to be higher, while it is lower for households that belong to religious or social groups, where cultural preferences may dictate choice of cooking fuel. Our results suggest that social networks play a critical role in dispersing information about LPG use, which we find to be an important source of spillovers in encouraging households to switch to clean energy sources.

This paper uses two sets of large-scale survey data on household-level consumer expenditure, which are nationally representative. The biggest benefit of using these data is that their large sample sizes allow us to compare the adoption of cooking fuels across all areas of the country, and across very heterogeneous sets of populations, both in terms of socio-economic characteristics, and governance. The first dataset is from the National Sample Survey (NSS) Household Consumer Expenditure, which comprises repeated cross-sections. The second is the India Human Development Survey (IHDS) Consumer Expenditure dataset, which is a two-year panel (2005-06 and 2011-12).

Our strategy in this paper is to provide multiple pieces of evidence, which, when taken together, provide complementary evidence on the presence of social spillovers in LPG use. Using the NSS data, we first estimate a linear probability model to study the determinants of a household's decision to use LPG as the primary cooking fuel, focusing mainly on the corresponding decision taken by other households in the same village, or urban block. Furthermore, we employ an instrumental variable linear probability model (IV-LPM) approach to control for potential endogeneity in this estimation. Using the IHDS data, we are able to incorporate household fixed effects, which help us to control for time-invariant unobserved heterogeneity. Our results are robust across specifications, and support the hypothesis of social spillovers in the use of LPG in the Indian context.

This paper contributes to the literature on the adoption (and use) of clean fuels in developing countries by investigating the extent to which social spillovers may affect the adoption of LPG in India. This paper is the first, to the best of our knowledge, to provide an empirical estimate for social spillovers in this context, and we do so with a credible empirical design. Focus on the use of LPG as a fuel ensures that we look at the continued use of clean cookstoves that burn LPG, which is the economic outcome of interest. As shown by Hanna et al. (2016), mere ownership of improved cookstoves does not necessarily imply that households will reap their health benefits. Regular use is important, which also requires that households maintain these cookstoves. While sources of fuel such as firewood are available freely, and at significantly lower costs, we provide evidence that households can be influenced by other households residing in the same village or urban block to purchase and regularly use cleaner cooking fuels.

These findings suggest the possibility that social interactions may explain the spatial disparities that are observed in the adoption of LPG in India. Our results are relevant to policy-makers operating in similar contexts and aiming at reducing the use of polluting cooking fuels, with subsidies or other measures. Based on our evidence, policy-makers may try to leverage existing social interactions, e.g. by targeting their interventions towards segments of society which are "influential", and thus likely to affect the behaviour of other households, especially if the extent to which learning occurs depends on the structure of the local social network (cf. Banerjee et al. 2014).

The structure of the paper is as follows: section 2 provides a background on cooking fuel use in India and a review of the literature, section 3 elaborates on our hypotheses and the data used to test them empirically, section 4 presents the empirical results and discuss potential policy implications, and section 5 concludes.

2 Background and Literature Review

2.1 Background on Cooking Fuel Use in India

Several sources of energy are used as cooking fuels in India, and the energy choice typically varies between rural and urban households. Rural households have strong preferences for biofuels such as firewood, charcoal and agricultural waste, whereas many urban households have switched to electricity, kerosene and LPG. Fuels derived from solid biomass such as firewood are not only cheaper (sometimes available for free) and more easily accessible, but they are also difficult to wean households off. According to data provided in the 2011 Census, almost 67% of the overall Indian population still relies on solid fuels such as firewood, crop residue, dung cakes and coal as the primary cooking fuel, and the proportion is almost 85% among rural households. This may be related to affordability and easy availability, but also to cooking habits and preferences, which have not changed significantly over time.

Ample scientific evidence suggests that burning traditional biomass as a cooking fuel in homes leads to indoor air pollution, and that fuels like LPG are much cleaner in terms of their environmental impact compared to sources such as firewood (Boy et al. 2000, Singh and Gundimeda 2014, WHO 2016). In this paper, we choose to restrict our attention to use of LPG as the clean cooking fuel alternative. This is because it is the most widely available clean cooking fuel in India, and the most affordable. LPG is currently being used by most urban households, and increasingly by many rural ones.

Acquiring an LPG connection requires a fixed cost to purchase the stove, and install the equipment. Households purchase gas cylinders as and when required. Income and awareness are thus obvious determinants of the choice of a household to consume cleaner fuels such as LPG. However, the shift to cleaner fuels may not necessarily follow the energy-ladder model, according to which households switch to cleaner cooking fuels in a linear way as the level of income increases. In this respect, we note that fuel-stacking is commonly observed amongst many Indian households, where a mixture of modern and traditional fuels are used simultaneously (Cheng and Urpelainen, 2014).

The energy transition has been more sustained in the urban sector than in the rural: in 1987, for instance, consumption of traditional biomass and LPG was not significantly different amongst rural and urban households, whereas in 2010, 60% of urban households used LPG, without simultaneously using biomass-based fuels, while only 10% of rural households did so (Cheng and Urpelainen, 2014). Rural households are often unable to afford the recurrent expenditures needed to acquire the cylinders, and also have difficulties in purchasing cookstoves. LPG users are also required to have a permanent and verifiable residential address, which limits the access of poor or homeless people, even in urban areas (Gupta and Kohlin, 2006). LPG is marketed by state-owned petroleum distribution companies, and its price is fixed by the Ministry of Petroleum and Natural Gas. The government has subsidised LPG (and kerosene) since the late 1960's, although in recent times efforts are being made to phase these subsidies out.

Nevertheless, while it seems that even though LPG is subsidised to meet the requirements of poor households, the benefits of these subsidies have largely accrued to the richer urban households. According to recent estimates, the top 20% of the population, by consumption expenditure, received 60% of the total direct subsidy, whereas the bottom 50% of the population received about 8% of the subsidy (IISD 2014). There are also disparities in the distribution of subsidies and LPG connections across Indian states. For instance, five states, Maharashtra, Andhra Pradesh, Tamil Nadu, Uttar Pradesh and Karnataka, account for around 50% of the total connections of LPG. The same five states, for instance, receive almost 50% of the subsidies, and, even within these states, the urban areas benefit the most (IISD 2014).

Recent reforms have been undertaken by governments to improve the accessibility of LPG to Indian consumers, both rural and urban, and to try to improve the provision of subsidies. However, either these reforms have often been punctuated with policy reversals, or they have not had considerable impact in improving the actual disbursement of subsidies.

For instance, in September 2012, the central government capped the number of subsidised cylinders that a household can acquire at six per year. On January 2013, however, the limit was increased to nine cylinders per household per annum, which was further increased to 12 by 2014. Governments have found it politically infeasible to initiate a phase-out of the subsidies, even though efforts are being made to allocate more resources towards poorer, rural households. For instance, in March 2015, the central government initiated a policy encouraging rich, urban consumers of LPG to voluntarily renounce their subsidies, which would free up resources for targeting subsidies to poor households. Following this announcement, almost two million households surrendered their rights to receive subsidies on LPG cylinders. Such measures have had some success in ameliorating the disparities that currently exist in securing access to LPG for all households in India.

In this paper we analyse whether the presence of social spillovers may justify additional initiatives targeting subsidies to specific sub-populations, and so increasing their effectiveness.

2.2 Literature Review

There is a growing literature looking at the adoption of clean cooking fuels and improved cookstoves (ICS) in developing countries, including in the Indian context. A significant strand of this literature has focused on air pollution borne out of the continuous use of solid biomass for cooking, and the associated negative health implications (Ezzati et al. 2000, Boy et al. 2000, Zhang and Smith 2007, Romieu et al. 2009). A key finding that has emerged is that insufficient use of ICS, and their improper maintenance, is prevalent in developing countries, which limits their health benefits. Mobarak et al. (2012), for instance, find from surveys in Bangladesh that households' willingness-to-pay for improved cookstoves is low, as households tend to underestimate the risk of ill-health from burning solid biomass (cf. also Greenstone and Jack 2015). This may lead to some households only using these stoves if they are provided for free, and thus limiting their regular use.

However, providing the stoves for free may also not be sufficient. In a recent paper, Hanna et al. (2016) use experimental data for India and find that distributing clean cookstoves to poor, rural households leads to lower pollution and improved health outcomes, but only in the short run. This result was borne by the fact that households in the sample were not maintaining the cookstoves, and used them irregularly. Regular maintenance of cookstoves is crucial to guarantee improved health outcomes (Duflo et al. 2008).

The second significant strand of the literature on cooking fuels and ICS has focused on the socio-economic determinants of the adoption of clean cooking fuels by households. Lewis and Pattanayak (2012) provide a comprehensive summary of several studies which have looked at the determinants of cooking fuel choice in low and middle-income countries. Income, education, and urbanisation are found to be the most common determinants of the choice to adopt clean cooking fuels, including in India, along with access to cleaner cooking fuels (Reddy 1995, Rao and Reddy 2007, Kumar and Viswanathan 2007, Farsi et al. 2007, Gupta and Kohlin 2006).

Another aspect of the transition to clean cooking fuels which has been studied in the Indian context is the phenomenon of fuel stacking: Cheng and Urpelainen (2014) find that from 1987 to 2010, many Indian rural households began to use LPG, but continued to use firewood as well. One of the most important reasons for this behaviour is the need to diversify and rely on multiple sources of cooking, hedging against variations in the price of the fuel and uncertainty in its supply.

Socio-economic determinants need not be the only factor influencing households' decision to adopt clean fuels (or clean technologies). In this respect, a growing literature has examined the role of social spillovers, or how the decisions of a household's neighbours, social network or friends may influence its own decisions, in the context of energy-related consumption choices. The literature on developed economies has looked at the role of spillovers, or "peer-effects", in explaining the adoption of green technologies like solar panels. Bollinger and Gillingham (2012) study the presence of peer effects in the diffusion of solar panels in California, and find that an additional solar panel in a given ZIP code is likely to increase the probability of adoption by households in the same ZIP code by 0.78%. The authors use the lag between the time of adoption and delivery of the panel for identifying the magnitude of this effect, and find that it increases over time. Graziano and Gillingham (2015) also study the diffusion of photovoltaic panels in Connecticut, and find a similar pattern. They also use a rich set of controls related to the built environment, and socio-demographic factors. Additional literature confirms the results for solar panels, and provides new evidence for other green technologies, such as hybrid cars (Carattini et al. 2017 provide a review).[4]

The literature on social spillovers in the adoption of new technologies in developing countries has mainly focused on agricultural issues. For instance, Munshi (2004) finds evidence of social learning amongst farmers in the adoption of high-yield varieties of rice and wheat in India. Bandiera and Rasul (2006) study the adoption decisions of farmers in Mozambique, and find that farmers are more likely to adopt a new crop if a few farmers in their network adopt, but it may no longer be in their interest to adopt it if too many farmers in their network do so.

Beltramo et al. (2015) is one of the few papers, to our knowledge, that studies the role of spillovers in clean technologies: they study the adoption of efficient cookstoves using data from a randomised control trial in Uganda, and do not find evidence of peer effects in the purchase decisions of households. They attribute this to the availability of other sources of information (other than word-of-mouth), and to the possibility that households may desire the stoves, but lack financial resources to be able to purchase them. Our paper, on the other hand, finds that while the latter may be true also in the Indian context, information flows do play an important role in purchase decisions of households.

Additional literature is covered in the next section, in which we distill our main hypotheses.

[4] The role of social networks has been studied extensively in the context of economic phenomena other than technology adoption; there is a branch of the literature on social capital which looks at whether membership in social organisations could play a role in increasing prosperity, for instance (cf. e.g Putnam et al. 1994, Knack and Keefer 1997)

3 Methodology

3.1 Hypotheses

In this section, we describe the main hypotheses that we aim to test in the empirical part of the paper. First, we expect higher adoption of LPG in areas wherein adoption is already relatively high. A vast empirical literature exists on the role of spillovers in new technology adoption, especially those related to agricultural and health innovations. Broadly, this literature has found that households are more likely to be influenced by other households, if they have strong information linkages with them (Conley and Udry, 2010) and if social interactions offer opportunities to learn how to use a product, rather than just influencing the desire to have it (Oster and Thornton, 2012). Households may also delay their decision to adopt a given technology, if they aim to free ride on others adopting early and generating opportunities for learning (Bandiera and Rasul, 2006). As a result, considering a relatively long time frame increases the relevance of the empirical analysis. In some cases, households may also delay adoption indefinitely, if other people's adoption create positive externalities from which they could benefit. For instance, Kremer and Miguel (2007) find amongst households in Kenya that adoption of de-worming drugs might be lower for certain households due to positive externalities across households. In the context of clean cooking fuels, the main benefits are related to indoor air pollution, which is a benefit that can be appropriated mostly by the members of a given households. Hence, we expect a positive relationship between past and current adoption, over the time frame considered.

Second, following also from the point above, we are interested in examining the dynamics of spillovers. Few studies thus far have been able to comment on the dynamic effects of spillovers (often due to a lack of suitable data). Oster and Thornton (2012) find, using data from Nepal, that peer effects in the adoption of menstrual cups amongst girls were significantly weaker in the last three months of the study, and thus peer effects are more likely to be important in the early months after recipients have been given a technology. They highlight that this is particularly relevant in scenarios where the adoption process is driven by flows of information about the product. Once all individuals know, eventually, about the product (and learn how to use it), the strength of the effect is likely to weaken. These findings have also been confirmed in the case of clean technologies in developed countries. Studies focusing on the diffusion of solar photovoltaic systems in the United States have found that while households are more likely to install panels if their neighbours also do so, the magnitude of this spillover effect may decrease with additional installations. Social interventions targeted specifically at leveraging peer effects can, however, reinvigorate these beneficial effects (Bollinger and Gillingham, 2012). Graziano and Gillingham (2015) find that while neighbourhood effects play a positive role in the adoption of panels by households in Connecticut, the strength of these effects is a negative function of the installation's vintage. That is, the ability for one installation to drive more installations decays over time. Absent any external intervention, the strength of social spillovers in the adoption of solar panels, for any given time frame and distance, decreases as the market reaches maturity, as evidence from Switzerland shows (Baranzini et al., 2017). These findings are likely to imply that, if they apply to our context, the strength of spillovers will be lower in areas that started out with higher rates of adoption of LPG. Moreover, they are also likely to imply that the strength of the spillover effect will decrease over time.

Third, an inference that can be drawn from the literature is that close social interaction (proxied for instance by participation in social networks) is more likely to lead to stronger flows of information across households (Bandiera and Rasul 2006, Oster and Thornton 2012). Munshi (2004) also finds, using data from the Green Revolution in India, that the more homogenous the population through which the technology diffuses, the stronger the information flows. Hence, we can hypothesise that flows of information will be stronger across households when they are closely knit. However, these dynamics may be very group-specific. For instance, it is plausible that membership in e.g. women's groups is more likely to be correlated with greater flows of information, given that women are more involved in cooking-related decisions. Stronger spillovers may also be expected for other types of networks, such as credit and savings organisations, or self-help groups, in which women often participate actively (especially in rural areas). In contrast, belonging to social groups with strong priors related to the use of clean cooking fuels (and, in general, to the role of traditions), may have the opposite effect. Rao and Reddy (2007) stress that culture and religion may be strongly correlated with household decisions in terms of energy consumption. In the Indian context, cultural preferences for food cooked in firewood may be stronger for households belonging to social or religious groups (Masera et al. 2000, Khandelwal et al. 2017).

Fourth, we are interested in examining whether peer effects are stronger for households that reside in rural areas, or in urban areas. While it is true that urban areas in India have higher population density than rural areas, this need not imply that the magnitude of spillovers is stronger for these households. There is some evidence, for instance, that social ties are stronger amongst households residing in rural areas, compared to urban areas (Green, 2013).

3.2 Data

The objective of the approach adopted in this paper is to provide multiple strands of evidence on the role of social spillovers in incentivising Indian consumers to adopt LPG, and thus to test the hypotheses that we derived in the previous section. We use two sets of data for the empirical analysis. The first set of data employed is from the National Sample Survey (NSS) of India, which is published by the National Sample Survey Organisation (NSSO), a subdivision of the Ministry of Statistics and Programme Implementation of the Indian government (Office), 2199). The NSSO has been conducting consumer expenditure surveys (CES) on an annual basis (barring some years) since 1983, thereby providing repeated cross sections. Each sample frame is designed to be representative, and comprises households in both the rural and urban areas of the country. The surveys include detailed expenditure data on food items, clothing and footwear, durables, medical and educational expenditure, and other items of daily use such as cooking and lighting fuel.

The NSSO conducts "thick" rounds of the NSS at a frequency of approximately every five years, whereas in the interim, "thin" rounds are conducted, wherein a smaller sample of households is surveyed. The thick rounds that are included in our analysis are the 43rd, 55th, 61st and 66th rounds of the surveys (corresponding to the years 1987-88, 1999-00, 2004-05 and 2009-10).

In the empirical estimations, we only use the thick rounds of NSS data to ensure that the sample size is sufficiently large (over 100,000 households) to provide ample geographical heterogeneity in the data, in order to examine spatial disparities. The NSS data allows us to attribute to each household the district and the state of residence. In addition, the NSS data provides us with coded information for the urban block or village to which each household belongs. From this, we are able to ascertain which households reside in the same village or urban block, without having to know the exact location of their residence (which is undisclosed due to data privacy concerns).

The second database we use in this paper is from the India Human Development Survey (IHDS), compiled by the University of Maryland and the National Council of Applied Economic Research (Desai and Vanneman 2009, Desai and Vanneman 2015). It is a panel dataset, with two rounds of data available (2005-06 and 2011-12). 83% of the households sampled in the first round also respond in the second round. The panel nature of the data enables us to track changes in LPG adoption over time. This panel dataset, composed of about 40,000 households, thus complements the larger cross sections of the NSS.

In both datasets, households are asked detailed questions about their expenditure on items over a "reference period", which is defined by the questionnaire for each item. The reference period often varies across items. For instance, for fuel-related expenditures, most of the rounds ask the households for expenditure over the previous 30 days.[5]

Our empirical approach uses data from the NSS on expenditures of all types of fuels purchased by the households, along with the respective quantities and amount spent on the purchases, and information on the primary fuel used by the household, both for cooking and lighting purposes. This information is particularly useful, given that fuel stacking is commonly observed amongst households in India, where multiple fuels are used at the same time. In the IHDS data, we restrict the sample to the households for whom we have valid information on whether or not they spent on the LPG fuel in the last 30 days, and amongst those that spent on LPG, those that primarily use the fuel for cooking purposes (instead of heating, or other purposes).

The measure of LPG adoption (our dependent variable) in the NSS data is a binary variable for whether LPG is the primary cooking fuel of a household or not. The IHDS data do not have the exact same variable. Our measure of adoption for this data is represented by whether the household spent on LPG in the last 30 days. Both variables eschew the possibility of irregular use of LPG, which may be a potential problem with using initial LPG adoption as a measure.

Table 1: Sample Size and LPG Adoption Rate by Village/Urban Block

Statistic	NSS				IHDS
Round	43	55	61	66 (Type 1)	Overall Panel
Year	1987-88	1999-00	2004-05	2009-10	2005-06 and 2011-12
Households sampled in village/urban block : Mean	9.95	11.96	9.98	7.98	33.88
Households sampled in village/urban block : Min.	2	2	3	2	4
Households sampled in village/urban block : Max.	10	12	10	8	88
LPG adoption rate at village/urban block level: Mean (%)	10.5	25.82	29.79	41.24	65.57
Observations	104874	103094	97998	67374	18179

Notes: Values reported are calculated only for observations included in the regression sample. Villages and urban blocks in the IHDS data comprise 150-200 households.

[5] The 66th round of the NSS comprises two sub-rounds of surveys, which differ in terms of the recall period for some of the items purchased; this was done by the NSS to investigate whether there is a tendency for households to underreport expenditures with a longer recall period. For instance, the first type of data in the 66th round uses a recall period of 30 days for food, beverages and tobacco expenditures, while the second type of data uses a recall period of 7 days for expenditure on the same items. To ensure comparability with the other rounds, we only use observations for which the 30-day window was used.

Table 1 provides information on the mean, maximum and minimum number of households by village or urban block in both datasets, and the mean LPG use rate (at the village/urban block level). Figure A1 in Appendix A shows the distribution of households by primary fuel-type (for cooking purposes) in the four thick rounds of the NSS. As it is clear from these graphs, firewood was, and still is, the primary cooking fuel for a majority of the households. The popularity of LPG has increased over this period, and as of 2010, it is the second most popular cooking fuel used by households. Kerosene has also gained in popularity in recent years, primarily in urban areas. Dung cakes have gained popularity in rural areas.

Figure A2 focuses on LPG only and plots the evolution of the proportion of households for whom LPG is the main cooking fuel, and shows how it has gained popularity, especially in recent periods. We also observe that the pace of increase in adoption has been much faster in urban areas, thus leading to a much larger share of LPG users in urban areas than in rural areas.

Figure A3 shows the regions which have contributed most to the increase in popularity of LPG. In 1987, the highest proportion of LPG users were in Delhi and the "union territories" of Goa, Chandigarh and Daman and Diu, which are all primarily urban areas. Over time, some of the bigger states, such as Maharashtra, Tamil Nadu, and Karnataka, experienced an increase in the share of LPG adopters.

Households are also asked about expenditure on durable goods (such as cookstoves) in the last 365 days. Both datasets compile information on the demographic characteristics of all households, including the age, gender, marital status, industry of occupation, and level of education. Information is also provided on land ownership (total land possessed, whether land is rented, irrigated, etc.), and the physical characteristics of the house (such as the type of structure, the condition of the house, type of floor, etc.).

Table 2 and Table 3 provide summary statistics on some of the demographic characteristics of the households using NSS and IHDS data, respectively. From Table 2, it is clear that the proportion of households using LPG as the primary cooking fuel has increased over time (from 10% in 1987-88 to 39% in 2009-10). Simultaneously, the proportion of households that have access to firewood has declined over the same period from 73% to 63%.[6]

The statistics presented in Table 3 suggest much higher rates of adoption of LPG compared to those in Table 22: the differences between the NSS data and the IHDS data can be attributed to the difference in the measure of adoption. In Table 3, we are considering whether a household spent on LPG, and not necessarily whether they used it as the primary cooking fuel, which is the reason for the difference in values in these two tables.[7]

Finally, Table 4 provides descriptive statistics, in terms of overall adoption and adoption by rural and urban households, respectively, for each social network considered in the IHDS and our paper. Based on the classifications available in the data, we consider the following social networks: women's groups, youth and sports associations, unions and business groups, self-help groups, credit and savings associations, religious and social groups, caste associations, developmental groups and NGOs, agricultural groups and cooperatives. As indicated by Table 4, there is a fair amount of variation among groups, especially in the rural context.

3.3 Empirical Approach

In order to investigate the presence of spillovers in LPG use, we adopt a multi-pronged approach by providing evidence from both cross-sectional and panel datasets on the hypotheses developed in the conceptual framework. In this section, we describe the econometric models that we estimate using both cross-sectional and panel data. Our first model uses cross-sectional data for testing the presence of social spillovers across households

[6] Another interesting finding to emerge from this table is the drop in the percentage of households that bought a new cookstove in the last 365 days: it declines from around 4% in 1987-88 to just about 1% in 2009-10. This may be attributed to the S-shaped nature of the diffusion process: with time, most households would have bought new cookstoves, thus the proportion of households that buy new cookstoves would decline.

[7] Households often spend on LPG, without using it as the primary cooking fuel(Cheng and Urpelainen, 2014).

Table 2: Summary Statistics of NSS Data

Round		43			55			61			66	
Year		1987-88			1999-00			2004-05			2009-10	
Variable	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs
LPG as primary fuel type (%)	10	29	127,932	23.94	42.67	119,639	28	45	124,637	39	49	100,845
Proportion of rural population (%)	64.65	47.81	118,205	59.40	49.11	119,638	63.62	48.11	124,637	58.62	49.25	100,845
Household size	5.1	2.74	127,932	4.99	2.65	119,638	4.89	2.52	124,637	4.65	2.34	100,845
Monthly per capita expenditure (Rs./month)	230.31	285.53	118,299	757.74	1059.2	119,639	851.51	1160.53	124,637	1527.90	1525.02	100,845
Age of head of households (years)	43.72	13.97	127,932	46.65	11.58	104,540	49.19	10.56	99,156	52.09	9.35	67,882
Whether household head is female (%)	10	30	127,932	8.8	28.33	119,639	9	29	124,637	8	28	100,845
Whether household head has at least primary education (%)	41	49	128,026	44.41	49.69	119,639	46	50	124,637	33	47	100,845
Whether household lives in a district adjoining a district with big urban centre (%)	69.78	45.92	118,299	68.42	46.48	119,639	64.63	47.81	124,637	65.42	47.56	100,845
Whether the household has access to electricity (%)	43	49	128,031	64.41	47.88	119,639	73	45	124,637	83	38	100,845
Whether the household purchased a cookstove in the last 365 days (%)	3.69	18.85	118,650	8.47	24.85	119,638	0.29	5.39	124,637	0.6	7.66	100,845
Average price of LPG (Rs./kilogram)	15.62	14.38	113,664	12.77	2.02	117,984	21.12	7.22	124,367	23.82	2.56	100,781
Average price of kerosene (Rs./kilogram)	2.83	0.62	128,039	4.28	20.26	119,626	11.93	68.43	123,638	10.80	1.65	100,079
Whether the household has access to firewood (%)	73	44	128,039	60.84	48.81	120,127	68	46	124,637	63	48	100,845

Table 3: Summary Statistics of IHDS Data (2005-06 and 2011-12)

Year	2005-06			2011-12		
Variable	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs
Whether household spent on LPG in the last 30 days (%)	59.5	49.1	22703	99.8	3.41	22781
Whether household has access to electricity (%)	95.9	19.8	20717	99.99	0.01	22781
Proportion of rural population (%)	60.6	48.9	22703	58	49.4	22781
Household size	5.79	2.95	22703	4.83	2.29	22781
Number of years of education for household head	8.72	4.9	22673	9.40	4.97	22772
Household Income (Rs./year)	67506.37	97836.31	22703	155057.3	261935.1	22781

Table 4: LPG Adoption Rates by Social Network

Type of groups	LPG Adoption Rates					
Subsample	Overall		Rural		Urban	
	Rate	Obs.	Rate	Obs.	Rate	Obs.
Women's groups	0.826	4,172	0.759	2,767	0.957	1,405
Youth and sports associations	0.837	2,160	0.721	1,102	0.957	1,058
Unions and business groups	0.897	2,718	0.808	968	0.947	1,750
Self-help groups	0.839	5,737	0.791	3,979	0.950	1,758
Credit and savings associations	0.822	4,426	0.744	2,871	0.964	1,555
Religious and social groups	0.764	6,789	0.656	4,103	0.931	2,686
Caste associations	0.718	4,720	0.608	2,994	0.909	1,726
Developmental groups and NGOs	0.968	2,673	0.948	1,577	0.997	1,096
Agricultural groups and cooperatives	0.638	1,331	0.545	1,018	0.939	313

Notes: Average LPG adoption rates per group are based on all periods in our panel.

located in the same geographical area, i.e. the same village or urban block.

Using data from the four thick rounds of the NSS, we first estimate for each round a linear probability model (LPM) of the form[8]:

$$A_i = \alpha_0 + \alpha_1 A_{-ij} + \alpha_2 X_i + \mu_i \tag{1}$$

for each round, where the dependent variable is denoted by A_i, a binary variable indicating whether LPG is the primary cooking fuel of household *i*, and the main independent variable is A_{-ij} , the average LPG adoption rate amongst all households (other

[8] For robustness, we also estimate a non-linear logit model (see Table B1 in the Appendix). Coefficients for the main variables of interest remain unchanged with respect to those obtained from the LPM. This is also valid for a probit model (all additional results are available by the authors upon request).

than household i) in village/urban block j. X_i denotes household-specific controls, such as household size, age, gender and the level of education of the head of the household, whether the household has access to electricity, firewood, monthly per capita expenditure (MPCE) dummies, and prices of LPG and kerosene. It also includes a control for whether the household resides in a district which is adjoining a large urban centre.[9,10] μ_i denotes the stochastic error term. Standard errors are clustered at the village/urban block level, in order to control for the possibility of errors being correlated across geographical units.

In this framework, potential threats to identification may be due to endogeneity, in particular in relation to the problem of "reflection" or "simultaneity" (Manski 1993, Manski 2000, Moffitt and Others 2001). When studying peers, it may indeed be hard to isolate the effect of agent *i* on agent *j*, independent of the effect of agent *j* on agent *i*. In addition, in spite of the large set of controls used in our specifications, common unobservable factors may, in principle, still affect the observed decision of households to adopt LPG. Lastly, there may be endogenous group formation, even though our detailed data should address most of the concerns on self-selection of peers.

To address potential threats to identification, we apply an instrumental variable approach following Duflo and Saez (2002), which is an adaptation of an earlier application of instruments used by Case and Katz (1991). Duflo and Saez (2002) study whether there are peer effects among colleagues in the same department of a university in participation in retirement plans, and find that the choice of employees to enrol in these plans, and the choice of vendor, were influenced by the decisions made by colleagues. To causally

[9] While electricity is not required for using a cookstove with an LPG cylinder, this variable is used as a proxy for economic development which could enable access to LPG. The urban centres that are chosen are the state capitals, and the tier-I and tier-II cities of the country (where a tier-I city is defined as a city with population > 4 million, while a tier-II city is defined as one with population between 1 and 4 million).

[10] The NSS data does not directly provide a variable for the price paid by consumers to purchase LPG. We derive it by dividing a household's expenditure on LPG by the quantity of LPG purchased by the household. However, this can only be observed for households that actually purchased LPG in the last 30 days, which may be a small fraction of households for several subsamples. In order to estimate this variable for other households, we follow the procedure outlined by Kumar and Viswanathan (2007), compute the average price in the district, and attribute this as a measure of price for the households for which this information is not available.

assess the existence of peer effects, they instrument average participation in each peer group by the salary or tenure structure of that group. We apply their insights, and use the proportion of population of each village (or urban block) belonging to the highest monthly per capita expenditure (MPCE) decile as an instrument for average LPG adoption at the village/urban-block level, which is the potentially endogenous variable in the second-stage.[11] The model that is estimated is thus the same as above, but A_{-ij} is treated as endogenous. We apply this approach to each of the four thick rounds of the NSS data.

To alleviate residual concerns with identification, we exploit the potential of the IHDS panel data to estimate a fixed-effect linear probability model. The model that we estimate is:

$$A_{it} = \alpha_0 + \delta_i + \alpha_1 A_{-ijt} + \alpha_2 X_{it} + \alpha_3 \tau_t + \mu_{it} \tag{2}$$

where A_{it} is a binary variable indicating whether household *i* spent on LPG in the last 30 days prior to the date of the survey in period *t*. δ_i is the household-specific fixed effect which captures time-invariant unobservable characteristics of every household.[12] The explanatory variable of interest is A_{-ijt} , the average LPG adoption rate amongst all households (other than household *i*) in village/urban block *j* in time period *t*. X_{it} now includes potentially time-varying household-level characteristics, such as the size of the household, level of education of the household head, and income deciles, along with dummies for religion and caste. τ_t denotes a time trend, while μ_{it} denotes the error term.

For the reasons mentioned before, we also estimate a panel IV-LPM model following Duflo and Saez (2002). In choosing the instruments, we adopt the same methodology as with the NSS estimations, i.e. we use the proportion of population in the same village or

[11] MPCE is found to be an important determinant of the choice of a household to adopt LPG, thus the average LPG adoption rate in the village or urban block is likely to be highly correlated with the proportion of the population that belongs to the highest MPCE decile.

[12] In order to be able to partially capture the effects of time-varying unobservables, we also estimate models using village-by-year time trends. These results are included in the Appendix in Table B5.

urban block belonging to the highest income deciles.[13]

In order to test our hypothesis concerning the dynamics of spillovers, we use the 61^{st} round of the NSS data (from 2004-05) which allows us to get a sense of the pre-sample trends in LPG adoption in different states of India (it represents the last round of the NSS just before the time period when the IHDS sample begins). Following the distribution as observed in the descriptive statistics of the NSS data, we create four dummies using the IHDS data: households living in states with adoption rates below 20%, between 20-30%, between 30-40% and more than 40%. We then interact these dummies with the observed level of adoption in the village or urban block, to analyse how the spillovers change across the different states. We then estimate a linear probability model with fixed effects to test whether the spillovers weaken over time.

Next, we estimate model (2) only for households that declare to participate in certain networks or social groups within the same village or urban block. We adopt the IV-LPM methodology for this estimation, and this model is useful in eliciting which types of social networks have facilitated the adoption of LPG amongst Indian households, and in which groups the effect is weaker.

Lastly, we estimate the models (1) and (2) for rural and urban sub-populations, and evaluate whether there is a systematic difference in the magnitude of the spillover across different subgroups of the Indian population.

4 Results

4.1 Empirical Results

This section presents the results of the empirical estimations. Table 5 presents the results of the models estimated using NSS cross-sectional data from the four thick rounds of

[13] We use the proportion of population belonging to the four highest income deciles. Note that a non-linear model such as probit or logit with fixed effects would be biased due to the incidental parameter problem.

the survey. This includes the estimations of the linear probability models (in the odd-numbered columns) and the coefficients of the instrumental variable probit models (in the even-numbered columns).[14]

Our variable of interest is the level of LPG use at the urban block or village level. In all rounds and specifications, we find that the coefficient of this variable is positive, and in many estimations, significant at the 1% level. This provides evidence in support of Proposition 1, which posits that social spillovers across households in LPG use are positive. The coefficients should be interpreted as follows: in the 43rd round, a one unit increase in the average village/urban-block LPG adoption rate increases the probability that household i adopts LPG by about 0.62 units in the LPM, and by about 1.75 units according to the IVM. In other words, if the share of households in a village using LPG increases from 0 to 100%, the probability of household i adopting LPG increases by 62 percentage points in the LPM. The results of Table 5 also suggest that the spillovers are larger in magnitude in the earlier rounds, and decrease with time.

We now present an overview of the results with regards to the control variables. All coefficients have the expected signs. We find that households with better access to electricity are more likely to adopt LPG. The variable for proximity to a big urban centre is insignificant in most specifications. We also find that households having heads that are older, female, or more educated are also more likely to use LPG as the primary cooking fuel. On the other hand, those facing a high price of LPG, or those with access to firewood, are less likely to use LPG. Our results also suggest that larger households are more likely to adopt LPG, a common yet not undisputed finding (Lewis and Pattanayak 2012 offer a discussion). In this model, we also control for income using dummies for monthly per capita expenditure deciles, which are significant in every round, and their sign suggests that richer households are more likely to adopt LPG. This supports previous findings in

[14] The results of the logit model are included in Table B1, and the first-stage results corresponding to the IV probit results of table 5 are included in Table B2. Table B3 include the results of estimating the instrumental variable linear probability models, while Table B4 includes the first-stage result corresponding to these results.

the literature, suggesting that income is an important determinant of the decision of a household to switch to cleaner cooking fuels.

Table 6 presents the estimation results using the IHDS panel data using household and year fixed effects.[15] The estimates of columns (1) and (2) in Table 6 indicate that the variable for average LPG adoption at the village/urban-block level has a positive coefficient, confirming the results of Table 5, and providing further evidence in support of our hypothesis. The coefficients are significant at the 1% level. The magnitude of the coefficient is comparable to those obtained using NSS data: as the share of LPG adoption increases from 0 to 100%, the probability of household i adopting LPG increases by about 90 percentage points in the LPM. In the IV-LPM, a similar change is related to about a 0.69 unit increase in the probability of household i spending on LPG.

The results on the controls corroborate those obtained using the NSS data. The results of columns (1) and (2) suggest that households with access to electricity, and with heads that are more educated, are more likely to adopt LPG, whereas larger households are less likely to do so.

In column (3) of Table 6, we include an interaction term between indicator variables for the levels of LPG adoption in 1999-2000, and our main independent variable. The results suggest that the spillover effects are significant at the 1% level, and that the highest magnitude of the spilllover is for those households that reside in states which start with LPG adoption rates in the "middle" of the distribution, namely between 30% and 40%. Next are those states which have the LPG adoption rates between 20% and 30% prior to the data sample period. The interaction term is weakest in the states that were observed to have relatively high rates of adoption, namely those with adoption rates greater than 40%. This pattern is compatible with the S-shaped diffusion curve observed for many technologies. At low levels of adoption, diffusion is relatively slow, but as adoption increases, forces of contagion kick in, and at moderate levels of adoption, diffusion becomes rela-

[15] The results of the random effects and population-averaged models are presented in Table B6 in the Appendix.

Table 5: NSS Data Linear Probability Model (LPM) and Instrumental Variable Probit Model (IVM) Results

Round	43		55		61		66	
Year	1987-88		1999-00		2004-05		2009-10	
Dep.Var.: Whether prim. cooking fuel of HH i is LPG	LPM	IVM	LPM	IVM	LPM	IVM	LPM	IVM
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Average LPG use rate (village/urban block)	0.619***	1.748***	0.468***	1.080***	0.353***	0.801***	0.341***	-0.472
	(0.007)	(0.140)	(0.007)	(0.158)	(0.007)	(0.270)	(0.007)	(0.435)
Whether bordering an urban centre?	-0.053***	0.085	-0.051	-0.038**	-0.131***	-0.259	-0.025	-0.043
	(0.013)	(0.159)	(0.065)	(0.021)	(0.060)	(0.194)	(0.045)	(0.278)
Whether HH has access to electricity?	0.037***	0.635***	0.040***	0.703***	0.035***	0.657***	0.037***	0.636***
	(0.002)	(0.029)	(0.003)	(0.024)	(0.003)	(0.028)	(0.004)	(0.036)
Whether HH lives in a rural area?	0.011***	-0.483***	-0.007	-0.249***	-0.011***	-0.323***	-0.001	-0.647***
	(0.002)	(0.034)	(0.003)	(0.045)	(0.003)	(0.075)	(0.004)	(0.111)
Whether HH purchased a cookstove in last 30/365 days?	-0.033***	-0.169***	-0.107***	-0.415***	-0.021	-0.066	0.006	0.088
	(0.006)	(0.035)	(0.005)	(0.026)	(0.022)	(0.116)	(0.017)	(0.097)
Household size	0.009***	0.128***	0.017***	0.119***	0.015***	0.102***	0.019***	0.107***
	(0.0003)	(0.004)	(0.0005)	(0.003)	(0.0005)	(0.003)	(0.0006)	(0.006)
Age of head of household	0.001***	0.018***	0.001***	0.009***	0.0008***	0.006***	0.0008***	0.005***
	(0.00007)	(0.001)	(0.00009)	(0.0006)	(0.0001)	(0.001)	(0.0001)	(0.0008)
Whether head of HH is female	0.006***	0.157***	0.021***	0.187***	0.013***	0.142***	0.011***	0.126***
	(0.002)	(0.034)	(0.003)	(0.023)	(0.003)	(0.021)	(0.004)	(0.023)
Whether head of HH is educated	0.041***	0.732***	0.089***	0.638***	0.083***	0.623***	0.100***	0.564***
	(0.002)	(0.027)	(0.002)	(0.017)	(0.002)	(0.017)	(0.003)	(0.021)
Price of LPG (Rs.)	-0.00003	0.0004	-0.010***	-0.042***	-0.0004**	-0.007***	-0.004***	-0.019***
	(0.0005)	(0.002)	(0.002)	(0.006)	(0.0002)	(0.002)	(0.001)	(0.005)
Price of Kerosene (Rs.)	0.004***	-0.009	0.00004	-0.0007	-0.00001**	-5.26	0.003	-0.005
	(0.001)	(0.018)	(0.00009)	(0.002)	(0.000006)	(4.17)	(0.002)	(0.010)
Whether HH has access to firewood	-0.134***	-1.147***	-0.229***	-1.084***	-0.396***	-1.600***	-0.435***	-1.874***
	(0.003)	(0.029)	(0.004)	(0.022)	(0.005)	(0.030)	(0.006)	(0.025)
Observations	104845	104148	102994	102994	97963	97933	67374	67372
R^2	0.4729		0.5775		0.6004		0.6381	
Wald test of endogeneity (Chi^2)		0.21		31.64		10.47		21.28
P-value		0.6438		0		0.0012		0

Notes: The proportion of population in the same village or urban block in the highest income decile is used as an instrument in even columns. The average marginal effect is reported for the IVM. For the IVM results, the Cragg-Donald F-statistics are consistently high, and surpass the rule-of-thumb bound of 10 proposed by **?** to identify weak instruments (first-stage results are provided in Table B2 in the Appendix). All specifications include dummies for MPCEs, and for belonging to districts, religion, and castes. The dummy for monthly per capita expenditure of the 10th decile is the variable of reference. Standard errors are clustered at the village/urban block level (reported in parentheses). *,** and *** respectively denote significance at 10%, 5% and 1% levels. The coefficient of the constant has not been reported. The variable "Whether HH purchased a cookstove in last 30/365 days" includes by design expenditure on repairs in the 55th round. The IVM in the 61st round does not include controls for religion, as they would prevent the convergence of the model.

tively fast. Once the level of adoption increases further, the market tends to be saturated, and diffusion rates flatten out.

Additionally, in columns (4) and (5), we provide separate results for the rural and urban sub-samples, respectively. These results suggest that the spillovers are stronger amongst rural households compared to urban households, regardless of their previous levels of LPG adoption, and that the magnitude of this effect decreases for states with higher prior levels of LPG adoption in both rural and urban areas (compared to those at the beginning of the diffusion process).[16]

Next, we analyse whether households active in the above-mentioned social networks are more likely to adopt LPG. Table 7, thus includes the results of the IV-LPM estimation for households belonging to each type of network. According to our hypothesis, the strength of the spillovers may be higher amongst households belonging to social networks, given that they are likely to experience deeper, and more persistent interactions amongst themselves. However, we may expect some specific social networks to be related to traditional cooking modes, and thus to be associated with a higher reticence in adopting LPG.

In column (1) of Table 7, we estimate model (2) for all households who declare that they do not belong to any of the above-mentioned social networks. We use these households as benchmark. In columns (2) to (10), we estimate separate models for each of the social networks in our data. Consistently with our previous estimations, the variable of interest is the average level of LPG adoption, for a given village, or urban block, among the members of the social network.

The magnitude of the coefficient for average LPG adoption is 0.711 in column (1), our benchmark, and is significant at the 1% level. In columns (2) to (10) we find some coefficients to be larger than the benchmark, but others to be smaller. Households who belong to women's associations, unions or business groups, self-help groups, credit and

[16] In columns (3) to (5) of Table 6, we report the final coefficients for four mutually exclusive and exhaustive categories of households, based on their adoption in 1999-2000, thus the coefficient for the average LPG use rate variable is absent.

Table 6: IHDS Data Baseline Results

Dependent Variable: Whether HH i spent on LPG in the last 30 days Column	LPM (1)	IV-LPM (Overall) 2nd-Stage (2)	LPM (Using 1999-00 NSS LPG Adoption Rates) (3)	LPM (Rural) (4)	LPM (Urban) (5)
Average LPG use rate (Village/ Urban Block)	0.903***	0.694***			
	(0.005)	(0.039)			
Avg. LPG Use Rate * Indicator for 1999-2000 LPG adoption rate less than 20%			0.899***	0.914***	0.846***
			(0.054)	(0.036)	(0.096)
Avg. LPG Use Rate * Indicator for 1999-2000 LPG adoption rate between 20-30%			0.905***	0.920***	0.817***
			(0.054)	(0.036)	(0.095)
Avg. LPG Use Rate * Indicator for 1999-2000 LPG adoption rate between 30-40%			0.908***	0.919***	0.794***
			(0.054)	(0.036)	(0.096)
Avg. LPG Use Rate * Indicator for 1999-2000 LPG adoption rate more than 40%			0.764***	0.817***	0.537***
			(0.054)	(0.036)	(0.094)
Whether HH lives in a rural area?	0.004	0.00005	0.004		
	(0.007)	(0.011)	(0.007)		
Whether HH had access to electricity?	0.141***	0.277***	0.143***	0.106***	0.395***
	(0.013)	(0.027)	(0.013)	(0.012)	(0.047)
Household size	-0.003***	-0.012***	-0.003***	-0.003***	-0.002*
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Number of Years of Education of Household Head	0.002***	0.004***	0.002***	0.003***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	41090	41090	41090	22732	17530

Notes: All specifications include household-level fixed effects and time trends. Results include dummies for income deciles. Controls are included for caste and religion in all specifications. For the results in column (2), the first-stage F statistics to check for weak instruments are higher than the **?** threshold values, and the value of 10 suggested by Staiger and Stock (1997) (cf. Table B7 in the appendix).*,** and *** respectively denote significance at 10%, 5% and 1% levels. The coefficients of the constant are not reported.

savings associations, caste associations and development groups or NGOs are associated to stronger social spillover effect than households who do not belong to any of those networks. Some coefficients are especially large, if compared to the benchmark. It is, for instance, the case for unions or business groups, self-help groups, or developmental groups and NGOs. It is reasonable to assume that these groups are particularly prone to technological change, and facilitate knowledge sharing on new technologies.

In contrast, the coefficient capturing social spillovers is weaker than the benchmark for households who belong to religious or social groups, youth or sports groups, as well as agricultural cooperatives. For the latter group, the coefficient for social spillovers is not significantly different from zero, leading us to conclude that, statistically speaking, there is no evidence of social spillovers among households belonging to agricultural cooperatives. Consistently with the descriptive statistics provided in Table 4, we consider these groups to be likely to hamper social spillovers in the adoption of clean technologies, most likely due to strong preferences over cooking choices and the survival of traditions. Evidence shows, for instance, that social and religious groups may be more likely to propagate food and dietary preferences, including the choice of fuel for cooking. Within these groups, there may be a strong bias in favour of using firewood or charcoal, since, using these fuels, food is perceived to 'taste better' (cf. Guruswamy 2015). Likewise, members of agricultural groups may have strong common preferences for firewood, which may explain the absence of any peer effect in LPG adoption for these households.

In terms of interpretation, it is difficult to ascertain the exact nature of these spillovers, given our data. However, it follows from the previous result that spillovers across households in some specific social networks may allow to address some general information asymmetries related with the use of clean cookstoves and fuels in general.

Finally, we test for heterogeneity in spillovers between rural and urban households. The results presented in columns (1) to (8) of Table 8 present the results of the NSS estimations, whereas columns (9) and (10) present the results derived from the IHDS data. Our hypothesis is that, while rural and urban households can both be expected to experience positive social spillovers, the effect may be stronger for rural areas, where households tend to be relatively newer to the fuel, and where the market may be further away from saturation.

The models in columns (1) to (8) are estimated using the LPM, whereas the models in columns (9) and (10) are estimated using the IV-LPM.[17].The results from columns (1), (3), (5) and (7) of Table 8 suggest that the spillovers are positive for rural households in all rounds of the NSS, but there is no monotonic trend in their magnitudes across rounds. For urban households, instead, social spillovers seem to be weakening over time, as suggested by columns (2), (4), (6), and (8). All these coefficients are significantly different from each other at the 5% level.

The results of columns (9) and (10), based on our panel data, suggest that the strength of spillovers is stronger in rural areas, compared to urban areas in 2005-06. As far as their evolution over time is concerned, the interaction terms with the dummy for the year 2011-12 are insignificant for both the rural and the urban sub-samples, leading us to nuance our conclusions about a potential weakening of spillovers in urban areas, as initially indicated by the NSS data.[18] That is to say, we find no evidence to suggest unequivocally that social spillovers either increase or decrease in terms of magnitude, in both urban and rural contexts. Overall, our results suggest that social spillovers still play an important role in both rural and urban contexts, which provides opportunities to policy-makers and practitioners alike to leverage them.

Robustness tests are provided in Table B5. In all models so far, we clustered standard errors at the village, or urban block, level. In Table B5, we estimate the panel IV-LPM

[17] The first-stage results for the models in columns (9) and (10) are similar to the results for the entire sample (in column (1) of Table B7). All additional tables are available by the authors upon request

[18] The results in column (9) show that amongst rural households, the spillovers are positive and significant at the 1% level in 2005-06, but the insignificance of the interaction term between the average adoption and the indicator for the year 2011-2012 suggests that the effect has not weakened over time. We get similar results for urban households; the results of column (10) highlight that the positive (and significant, but smaller) spillover effect in 2005-06 is no different than the size of the effect in 2011-12 (again suggested by the insignificance of the interaction term).

Table 7: IHDS Data Social Network (IV-LPM) Results

Dependent Variable: Whether HH i spent on LPG in last 30 days	No network	Women's groups	Youth or sports groups	Unions or business groups	Self-help groups	Credit and savings groups	Religious or social groups	Caste associations	Developmental groups/NGOs	Agricultural cooperatives
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Average LPG use rate	0.711***	0.761***	0.483***	0.994***	0.871***	0.715***	0.667***	0.730***	0.943***	0.244
	(0.072)	(0.068)	(0.191)	(0.162)	(0.124)	(0.080)	(0.101)	(0.101)	(0.131)	(0.345)
Whether household is rural	-0.055*	0.073	0.020	0.028	0.025	0.017	0.012	-0.001	-0.116***	0.004
	(0.031)	(0.062)	(0.027)	(0.063)	(0.058)	(0.027)	(0.020)	(0.030)	(0.045)	(0.175)
Whether HH had access to electricity	0.270***	0.286***	0.445***	0.107	0.203***	0.299***	0.279***	0.263***	0.403***	0.709****
	(0.049)	(0.056)	(0.159)	(0.127)	(0.077)	(0.062)	(0.070)	(0.067)	(0.120)	(0.127)
Household size	-0.014***	-0.014***	-0.014***	-0.007**	-0.003	-0.013***	-0.021***	-0.015***	-0.010	-0.057***
	(0.003)	(0.003)	(0.006)	(0.004)	(0.007)	(0.005)	(0.004)	(0.005)	(0.006)	(0.022)
Number of Years of Education of Household Head	0.004***	0.006***	0.007**	0.003	0.002	0.004**	0.005***	0.007***	0.006*	0.016***
	(0.001)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)	(0.007)
Observations	9582	3864	5622	18536	8550	12166	7868	3272	1476	

Notes: Second-stage estimations are provided (first-stage results can be provided on request). Instruments are the proportion of households belonging to the highest income deciles in the same village or urban block (7th decile onwards). All specifications include household-level fixed effects and time trends. All specifications include dummies for income deciles, and controls for caste and religion. *,** and *** respectively denote significance at 10%, 5% and 1% levels. Standard errors are clustered at the village/urban-block level. The coefficient of the constant has not been reported.

Table 8: NSS and IHDS Results on Rural and Urban Households

Data	NSS								IHDS	
Year	1987-88		1999-00		2004-05		2009-10		2005-06 and 2011-12	
Round	43		55		61		66		Panel Data	
Dep.Var.: Whether prim. cooking fuel of HH *i* is LPG (NSS) or whether HH *i* spent on LPG in the last 30 days (IHDS)	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Average LPG use rate (village/urban block)	0.425***	0.506***	0.538***	0.431***	0.368***	0.270***	0.400***	0.239***	0.725***	0.592***
	(0.031)	(0.009)	(0.013)	(0.009)	(0.011)	(0.011)	(0.011)	(0.011)	(0.061)	(0.097)
Average LPG use rate * 2011 indicator									0.008	-0.054
									(0.029)	(0.079)
Whether bordering an urban centre?	-0.038	-0.006	-0.002	-0.023***	-0.138	-0.054	-0.045	-0.169		
	(110.147)	(0.024)	(0.002)	(0.006)	(0.100)	(0.053)	(0.074)	(0.146)		
Whether HH has access to electricity?	0.018***	0.053***	0.031***	0.088***	0.029***	0.076***	0.022***	0.097***	0.226***	0.505***
	(0.0014)	(0.004)	(0.002)	(0.006)	(0.003)	(0.007)	(0.004)	(0.010)	(0.038)	(0.055)
Whether HH purchased a cookstove in last 30/365 days?	0.007	-0.058***	-0.034***	-0.135***	0.003	-0.046	0.001	0.016		
	(0.007)	(0.007)	(0.005)	(0.007)	(0.027)	(0.036)	(0.020)	(0.029)		
Household size	0.001***	0.028***	0.006***	0.039***	0.009***	0.030***	0.015***	0.027***	-0.014	-0.006
	(0.0002)	(0.0009)	(0.0004)	(0.001)	(0.0005)	(0.001)	(0.0007)	(0.001)	(0.004)	(0.002)
Age of head of household	0.0001***	0.004***	0.0004***	0.002***	0.0004***	0.001***	0.0008***	0.001***		
	(0.00004)	(0.0002)	(0.00008)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0002)		
Whether head of HH is female	0.0007	0.014***	0.009***	0.040***	0.005	0.029***	0.005	0.026***		
	(0.001)	(0.006)	(0.003)	(0.006)	(0.003)	(0.006)	(0.005)	(0.006)		
Whether head of HH is educated	0.013***	0.088***	0.057***	0.138***	0.066***	0.121***	0.093***	0.116***		
	(0.001)	(0.004)	(0.002)	(0.005)	(0.003)	(0.005)	(0.004)	(0.006)		
Price of LPG	-0.0002	0.00001	-0.001**	-0.0126***	-0.0002***	-0.002**	-0.00003	-0.007***		
	(0.002)	(0.0005)	(0.0007)	(0.002)	(0.00008)	(0.0009)	(0.002)	(0.001)		
Price of kerosene	0.002*	0.012***	0.00003	-0.0004	-0.000005	-0.00001	0.002	0.003		
	(0.001)	(0.003)	(0.00008)	(0.0005)	(0.00001)	(0.000004)	(0.002)	(0.004)		
Whether HH has access to firewood	-0.050***	-0.194***	-0.162***	-0.248***	-0.372***	-0.413***	-0.440***	-0.435***		
	(0.004)	(0.005)	(0.006)	(0.006)	(0.0072)	(0.007)	(0.008)	(0.008)		
Number of years of education of household head									0.005***	0.002**
									(0.001)	(0.001)
Observations	65307	39567	61097	41897	62937	35026	39915	27459	22372	17530

Notes: The specifications using NSS data include dummies for MPCEs, and for belonging to districts, religions and castes. Columns (1) and (2) represent an exception, where religion dummies are not included, as they would prevent the convergence of the model. The results of columns (9) and (10) include household-level fixed effects and time trends. Standard errors are clustered at the village/urban block level (reported in parentheses). *,** and *** respectively denote significance at 10%, 5% and 1% levels. The coefficient of the constant has not been reported. The variable "Whether HH purchased a cookstove in last 30/365 days" includes expenditure on repairs in the 55th round.

and include village-specific fixed effects, and village-by-year interactions. First-stage estimations are provided in Table B7. Village-specific, rather than individual-specific, fixed effects capture time-invariant characteristics of the village (or urban block), which may relate for instance with supply of LPG. General trends may interact with these characteristics, hence the village-by-year dummy variables. Our main findings are robust to these additional specifications. In Table B5, the coefficient for average adoption of LPG in the village/urban block is positive and significant at the 1% level.

4.2 Policy Implications

Important policy implications can be derived from our results. We find that there are positive social spillovers in the decision to use LPG between households residing in the same village or urban block. Our results rely on several specifications and use both cross-sectional and panel data. We control for several factors that have already been proved to be critical determinants of LPG use in the literature, and we hypothesise that social interactions (through membership in specific social networks, for example) may play an important role in facilitating the adoption of clean cooking fuels.

Additionally, we find that these spillovers vary across rural and urban areas. We provide evidence that social spillovers exist for both, and they are stronger for rural households, an effect that persists over time. This suggests that while LPG has diffused across Indian households, in both rural and urban contexts there is still potential for informational spillovers in determining household fuel choice.

This paper finds that social spillovers are weaker for households residing in states that have higher LPG adoption rates, in line with the S-shaped diffusion model of technology. States with higher initial rates of adoption experience, over time, weaker spillover effects, in contrast to states that are at an earlier stage of the adoption curve. This information can be very precious to policy-makers, as the same intervention may have different degrees of cost-effectiveness, depending on the state's situation with respect to the S-shaped curve.

We also attempt to investigate whether these social spillovers exist amongst households having stronger social interactions, through membership in networks for instance. We define households who do not belong to any of the social networks examined in our data as benchmark. We find that some social networks are associated with stronger spillovers than the benchmark, while others are associated with weaker spillovers. These differences seem to be due to the type of social network analysed. Stronger spillovers are found among social groups that may see technological progress and innovation favourably. Weaker spillovers are found among social groups that may be associated with more conservative values and tradition, especially as far as cooking styles are concerned. These findings are very relevant for policy-makers. First, they point to cultural barriers in the adoption of LPG. Second, understanding how social norms work, within groups, and how social networks are structured, may allow policy-makers and practitioners to realize significant savings by implementing targeted interventions. That is, policy-makers can turn to their advantage the fact that different social groups may have different social norms, and that different social groups may have different social network structures.

Additionally, the finding of this paper about the effectiveness of specific types of networks (such as women's groups, self-help groups and credit and savings associations) in facilitating LPG adoption by households is important, not only for identifying channels through which information propagates quicker, but also for pinpointing which groups may need additional incentives to switch to cleaner energy sources (for instance, households that have members participating in agricultural groups or cooperatives that have better access to firewood).

Finally, we note that this paper does not provide any direct evidence either supporting or refuting the effectiveness of subsidies in encouraging Indian households to adopt LPG. Given that the Indian government has been looking to phase out these subsidies for a while, it remains to be seen whether spillovers would still exist, in their absence. However, if social spillovers are a factor in determining a households's choice of cooking fuel, subsidies to certain households in the early phases of the adoption process may actually be beneficial in ensuring that more households switch to the cleaner fuel.

5 Conclusion

Greater adoption of clean cooking fuels like LPG by the Indian population is vital for achieving a sustained reduction in indoor air pollution, and thus ensuring the consequent improvement of respiratory health. This paper analyses whether there are social spillovers in the adoption of LPG in India, and if these exist, how they vary in strength across varied sub-populations. We use two sources of data spanning a widely heterogenous population, a repeated cross-section and a panel dataset, which enable us to provide a broad scope in addressing this research question. We provide multiple pieces of evidence suggesting that social spillovers are present in the adoption of LPG in India, and that social networks play an important role in the dissemination of information across households. We control for several household-level characteristics of LPG adoption that have been shown to be important determinants in the literature, and address potential threats to identification. Our results may have strong implications for policy-makers looking to encourage consumers to switch to cleaner sources of energy in developing countries. We provide evidence suggesting that information flows amongst consumers of energy products are present in developing countries, and could be used as a policy measure by governments looking to hasten the switch to cleaner sources of energy.

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Appendix A Figures

Figure A1: Distribution of Households by Primary Cooking Fuel Type (Source: NSS)

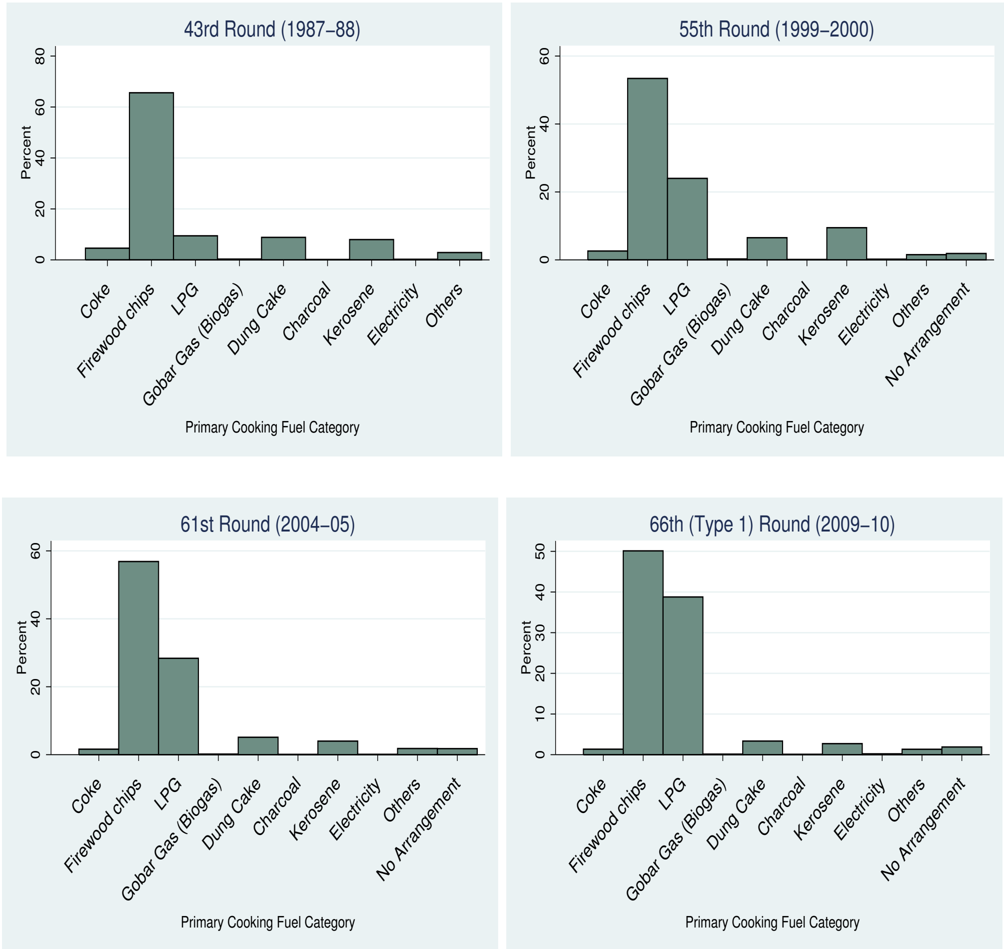


Figure A2: Population Share (%) Using LPG as the Primary Cooking Fuel: 1983 to 2011-12 (Source:NSS)

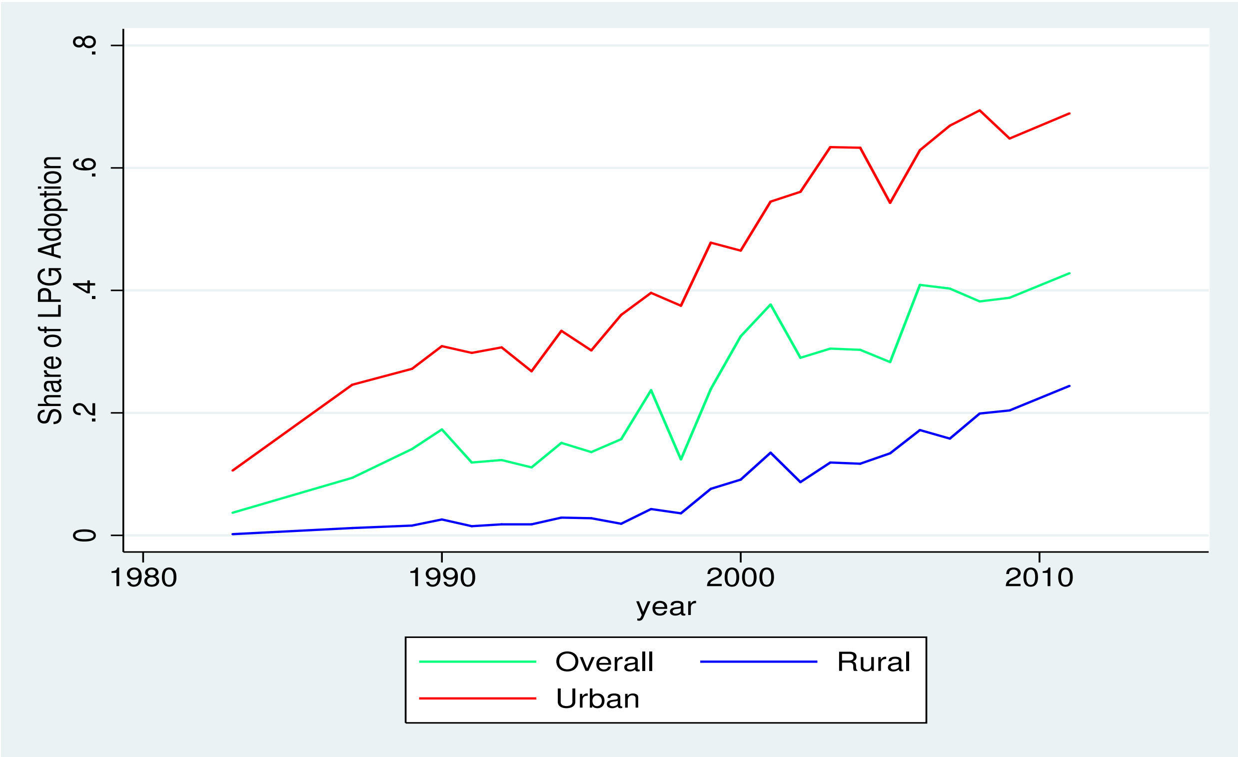
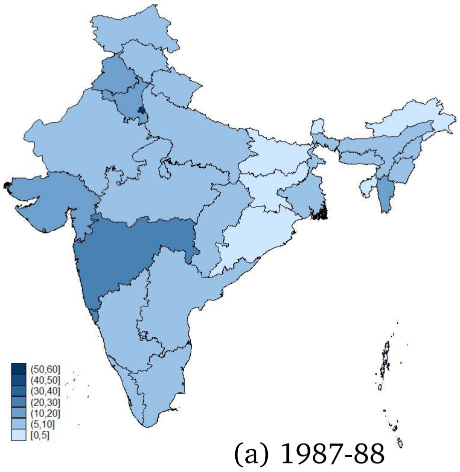
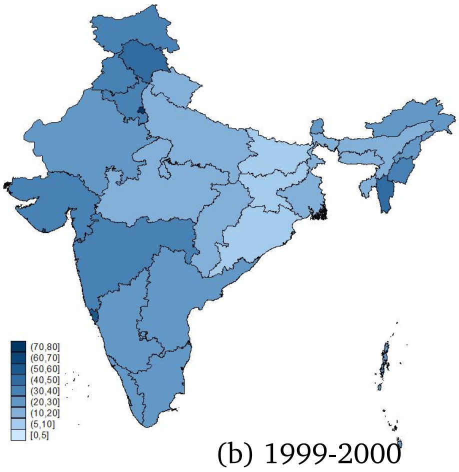


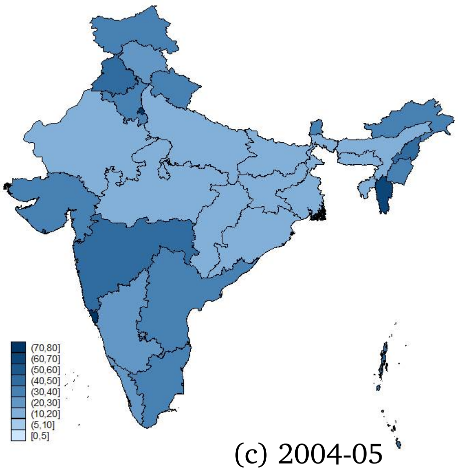
Figure A3: Share of Households Using LPG as the Primary Cooking Fuel (By State)
(Source:NSS)



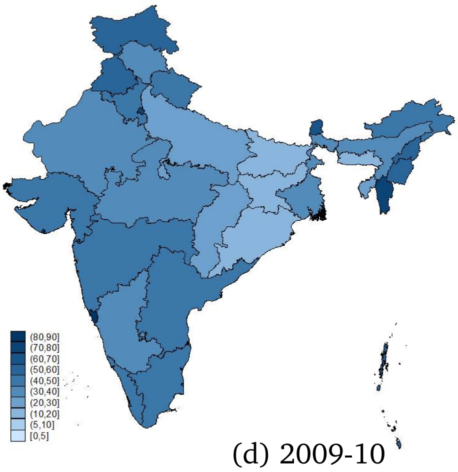
(a) 1987-88



(b) 1999-2000



(c) 2004-05



(d) 2009-10

Notes: The maps show the proportion of households (by state) for whom LPG was the primary cooking fuel in the 43^{rd}, 55^{th}, 61^{st} and the 66^{th} rounds of the NSS

Appendix B Tables

Table B1: NSS Data: Logit Estimations

Round	43	55	61	66
Year	1987-88	1999-00	2004-05	2009-10
Dep.Var.: Whether prim. cooking fuel of HH *i* is LPG	(1)	(2)	(3)	(4)
Average LPG use rate (village/urban block)	0.170***	0.280***	0.343***	0.365***
	(0.003)	(0.005)	(0.007)	(0.007)
Whether bordering an urban centre?	0.298	-0.298**	-0.247**	-0.092
	(0.195)	(0.157)	(0.131)	(0.146)
Whether HH has access to electricity?	0.441***	0.528***	0.557***	0.498***
	(0.019)	(0.020)	(0.024)	(0.032)
Whether HH lives in a rural area?	-0.572***	-0.159***	-0.080***	-0.053***
	(0.037)	(0.020)	(0.019)	(0.018)
Whether HH purchased a cookstove in last 30/365 days?	-0.010***	-0.051***	-0.0002	0.0002
	(0.002)	(0.003)	(0.0004)	(0.0005)
Household size	1.140***	0.950***	0.710***	0.656***
	(0.034)	(0.024)	(0.021)	(0.021)
Age of head of HH	1.327***	0.578***	0.380***	0.293***
	(0.060)	(0.041)	(0.042)	(0.049)
Whether head of HH is female	0.023***	0.027***	0.020***	0.012
	(0.006)	(0.003)	(0.003)	(0.003)
Whether head of HH is educated	0.529***	0.338***	0.357***	0.187***
	(0.018)	(0.009)	(0.010)	(0.006)
Price of LPG	0.014	-0.680***	-0.187**	-0.463***
	(0.040)	(0.134)	(0.092)	(0.121)
Price of kerosene	-0.052	-0.005	-0.001	-0.013
	(0.082)	(0.013)	(0.001)	(0.117)
Whether HH has access to firewood	-1.579***	-1.199***	-1.685***	-1.663***
	(0.037)	(0.023)	(0.025)	(0.026)
Observations	104177	102728	97930	67372
Pseudo R^2	0.6093	0.6046	0.6022	0.6234

Notes: Values reported are average marginal effects. All specifications include dummy variables for districts, MPCE deciles, religion and caste (except for the 43rd round, where the religion and caste dummies are are not included, as they would prevent the convergence of the model). Standard errors are clustered at the village/urban block level (reported in parentheses). *,** and *** respectively denote significance at 10%, 5% and 1% levels. The coefficient of the constant has not been reported.

Table B2: NSS Data: First-Stage Estimations

Round	43	55	61	66
Year	1987-88	1999-00	2004-05	2009-10
Corresponding Second-Stage Results (in Table 4)	Column (2)	Column (4)	Column (6)	Column (8)
Dependent Variable: Average village/urban block LPG use rate	(1)	(2)	(3)	(4)
Proportion of population in 10^{th} income decile	0.508***	0.539***	0.429***	0.303***
	(0.028)	(0.019)	(0.004)	(0.019)
Whether bordering an urban centre?	-0.113***	0.023***	-0.009	0.051
	(0.022)	(0.004)	(0.067)	(0.058)
Whether HH has access to electricity?	0.030***	0.046***	0.038***	0.052***
	(0.002)	(0.003)	(0.003)	(0.004)
Whether HH lives in a rural area?	-0.130***	-0.265***	-0.284***	-0.300***
	(0.003)	(0.005)	(0.005)	(0.005)
Whether HH purchased a cookstove in last 30/365 days?	0.00008	-0.027***	0.006	0.037***
	(0.008)	(0.006)	(0.011)	(0.017)
Household size	0.0009***	0.002***	-0.001***	-0.0004
	(0.0003)	(0.0003)	(0.0003)	(0.0004)
Age of head of HH	0.0009***	0.0004***	0.0004***	0.0003***
	(0.00006)	(0.00007)	(0.00006)	(0.0001)
Whether head of HH is female	0.008***	0.018***	0.016***	0.025***
	(0.002)	(0.003)	(0.002)	(0.003)
Whether head of HH is educated	0.027***	0.035***	0.025***	0.029***
	(0.001)	(0.002)	(0.002)	(0.003)
Price of LPG	-0.0003	-0.005***	0.006	-0.002**
	(0.0004)	(0.0008)	(0.071)	(0.0009)
Price of kerosene	-0.005***	0.0002	0.006***	-0.002
	(0.001)	(0.0002)	(0.003)	(0.002)
Whether HH has access to firewood	-0.084***	-0.110***	-0.134***	-0.174***
	(0.003)	(0.004)	(0.004)	(0.005)
Observations	104148	102994	97933	67372
5% maximal IV relative bias (?)	19.28	19.28	19.28	19.28
10% maximal IV size (?)	29.18	29.18	29.18	29.18
Cragg Donald F-Statistic	6654.707	3806.454	2363.815	597.317
P-value	0	0	0	0

Notes: All specifications include MPCE, district, religion and caste dummies. Standard errors are clustered at the village/urban block level (reported in parentheses). *,** and *** respectively denote significance at 10%, 5% and 1% levels. The coefficient of the constant has not been reported.

Table B3: NSS Data: IV Linear Probability Model Estimations (Second-Stage)

Round	43	55	61	66
Year	1987-88	1999-00	2004-05	2009-10
Dep.Var.: Whether prim. cooking fuel of HH *i* is LPG	(1)	(2)	(3)	(4)
Average LPG use rate (village/urban block)	0.828***	0.317***	0.097**	-0.132**
	(0.025)	(0.027)	(0.044)	(0.064)
Whether bordering an urban centre?	-0.027**	-0.005*	-0.071**	0.014
	(0.012)	(0.003)	(0.035)	(0.060)
Whether HH has access to electricity?	0.031***	0.055***	0.045***	0.061***
	(0.002)	(0.003)	(0.003)	(0.005)
Whether HH lives in a rural area?	0.040***	-0.050***	-0.084***	-0.144***
	(0.004)	(0.008)	(0.013)	(0.020)
Whether HH purchased a cookstove in last 30/365 days?	-0.032***	-0.104***	-0.020	0.022
	(0.005)	(0.005)	(0.022)	(0.020)
Household size	0.009***	0.017***	0.015***	0.019***
	(0.0003)	(0.0005)	(0.0005)	(0.001)
Age of head of HH	0.001***	0.001***	0.001***	0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Whether head of HH is female	0.004*	0.022***	0.017***	0.023***
	(0.002)	(0.003)	(0.003)	(0.004)
Whether head of HH is educated	0.035***	0.096***	0.089***	0.115***
	(0.002)	(0.003)	(0.003)	(0.004)
Price of LPG	0.394	-0.007***	-0.0004**	-0.005***
	(4.960)	(0.001)	(0.0002)	(0.001)
Price of kerosene	0.005***	0.432	-0.011*	0.001
	(0.001)	(10.600)	(0.006)	(0.002)
Whether HH has access to firewood	-0.115***	-0.233***	-0.430***	-0.518***
	(0.004)	(0.005)	(0.008)	(0.012)
Observations	104845	102994	97963	67374

Notes: All specifications include dummy variables for districts, MPCE deciles, religion and caste. Standard errors are clustered at the village/urban block level (reported in parentheses). *,** and *** respectively denote significance at 10%, 5% and 1% levels. The coefficient of the constant has not been reported.

Table B4: NSS Data: IV Linear Probability Model Estimations (First-Stage)

Round	43	55	61	66
Year	1987-88	1999-00	2004-05	2009-10
Dep.Var.: Average LPG use rate (village/urban block)	(1)	(2)	(3)	(4)
Proportion of population in 10th income decile	0.502***	0.540***	0.425***	0.303***
	(0.028)	(0.019)	(0.020)	(0.019)
Whether bordering an urban centre?	-0.113***	0.022***	-0.015	0.051
	(0.022)	(0.004)	(0.067)	(0.060)
Whether HH has access to electricity?	0.029***	0.046***	0.038***	0.052***
	(0.002)	(0.003)	(0.003)	(0.004)
Whether HH lives in a rural area?	-0.130***	-0.265***	-0.285***	-0.300***
	(0.003)	(0.005)	(0.005)	(0.005)
Whether HH purchased a cookstove in last 30/365 days?	-0.001	-0.027***	0.008	0.037**
	(0.008)	(0.006)	(0.011)	(0.017)
Household size	0.001***	0.002***	0.058**	-0.0004
	(0.0003)	(0.0003)	(0.030)	(0.0004)
Age of head of HH	0.001***	0.398	0.341***	0.0003***
	(0.00006)	(0.069)	(0.067)	(0.0001)
Whether head of HH is female	0.008***	0.018***	0.017***	0.025***
	(0.002)	(0.003)	(0.002)	(0.003)
Whether head of HH is educated	0.027***	0.035***	0.023***	0.029***
	(0.001)	(0.002)	(0.002)	(0.003)
Price of LPG	-0.392	-0.005***	0.606	-0.002**
	(0.377)	(0.001)	(7.320)	(0.001)
Price of kerosene	-0.006	0.159	0.621**	-0.002
	(0.001)	(0.123)	(0.309)	(0.002)
Whether HH has access to firewood	-0.084***	-0.110***	-0.133***	-0.174***
	(0.003)	(0.004)	(0.004)	(0.005)
Observations	104845	102994	97963	67374
5% maximal IV relative bias	16.38	16.38	16.38	16.38
10% maximal IV relative bias	8.96	8.96	8.96	8.96
Cragg Donald F-Statistic	332.386	829.314	469.302	251.903
P-value	0	0	0	0

Notes: All specifications include dummy variables for districts, MPCE deciles, religion and caste. Standard errors are clustered at the village/urban block level (reported in parentheses). *,** and *** respectively denote significance at 10%, 5% and 1% levels. The coefficient of the constant has not been reported.

Table B5: IHDS Data: Second-stage Estimations Using Village FE and Village-by-Year Time Trends

Dependent Variable: Whether HH *i* spent on LPG in last 30 days Column	Village FE (1)	Village-By-Year Time Trends (2)
Average LPG use rate (village urban block)	0.932***	0.934***
	(0.050)	(0.054)
Whether HH Lives in a rural area	0.029**	0.034***
	(0.014)	(0.015)
Whether HH has access to electricity?	0.123***	0.118***
	(0.027)	(0.029)
Household size	-0.004***	-0.004***
	(0.001)	(0.001)
Number of years of education of HH head	0.008***	0.008***
	(0.0003)	(0.003)
Observations	43179	43149

Notes: Results in column (1) include a time trend. All specifications include income decile dummies and controls for religion and caste. *,** and *** respectively denote significance at 10%, 5% and 1% levels. The coefficient of the constant has not been reported.

Table B6: IHDS Data: Random Effects and Population-Averaged Models

Dependent Variable: Whether HH *i* spent on LPG in last 30 days Column	Random Effects (1)	Population-Averaged Model (2)
Average LPG use rate (village/urban block)	0.879***	0.877***
	(0.005)	(0.005)
Whether HH lives in a rural area?	0.020***	0.020***
	(0.001)	(0.002)
Whether HH has access to electricity?	0.120***	0.119***
	(0.012)	(0.009)
Household size	-0.004***	-0.004***
	(0.001)	(0.0005)
Number of years of education of HH head	0.006***	0.006***
	(0.0003)	(0.0002)
Observations	43179	43179
Wald χ^2	111976.41	90640.17
P-Value	0	0

Notes: Both specifications include a time trend. Income decile dummies and controls for religion and caste are included in both models. Standard errors are clustered at the village/urban block level in the random effects model, while robust standard errors are estimated for the population-averaged model. *,** and *** respectively denote significance at 10%, 5% and 1% levels. The coefficient of the constant has not been reported.

Table B7: IHDS Data: First-Stage Estimations

Corresponding Second-Stage Results Column	Table 6 Column (2) (1)	Table B5 Column (1) (2)	Table B5 Column (2) (3)
Income: 7th Decile	-0.349***	-0.230***	-0.242***
	(0.081)	(0.044)	(0.045)
Income: 8th Decile	-0.498***	-0.296***	-0.292***
	(0.081)	(0.036)	(0.037)
Income: 9th Decile	-0.602***	-0.316***	-0.318***
	(0.084)	(0.032)	(0.034)
Income:10th Decile	-0.587***	-0.223***	-0.208***
	(0.057)	(0.022)	(0.023)
Whether HH lives in a rural area?	-0.020	-0.100***	-0.107***
	(0.037)	(0.009)	(0.010)
Whether HH has access to electricity?	0.651	0.512***	0.506***
	(0.021)	(0.010)	(0.011)
Household size	-0.044***	-0.023***	-0.023***
	(0.002)	(0.001)	(0.001)
Number of years of education of HH head	0.010***	-0.002***	-0.002***
	(0.001)	(0.0004)	(0.0004)
Observations	41090	43179	43149
5% maximal IV relative bias	16.85	16.85	16.85
10% maximal IV relative bias	10.27	10.27	10.27
Kleibergen-Paap Wald rK F-Statistic	46.468	76.169	67.974
P-value	0	0	0

Notes: Dependent variable for the models in columns (1), (2) and (3) is the average village/urban block level LPG use rate for all households other than household *i*. Results in column (1) includes household fixed effects and a time trend, the results in column (2) include village-level fixed effects and a time trend, and the results in column (3) include village-by-year time trends. Exogenous instruments for the results in all columns are the proportion of population (by village) belonging from the 7^{th} to the 10^{th} income deciles. All specifications include income decile dummies. Controls for religion and caste are included in all specifications. *,** and *** respectively denote significance at 10%, 5% and 1% levels. The coefficient of the constant has not been reported.