Electric stoves as a solution for household air pollution: Evidence from rural India

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Abstract

We collected minute-by-minute data on electricity availability, electric induction stove use, and kitchen and outdoor particulate pollution in a sample of rural Indian households for one year. Using within household-month variation generated by unpredictable outages, we estimate the effects of electricity availability and electric induction stove use on kitchen PM2.5 concentration at each hour of the day. Electricity availability reduces kitchen PM2.5 by up to 50 $\mu g/m^3$, which is between 10 and 20 percent of peak concentrations during cooking hours. Induction stove use instrumented by electricity availability reduces PM2.5 in kitchens by 200-450 $\mu g/m^3$ during cooking hours.

Keywords: household air pollution, indoor air pollution, induction cookstoves, electricity reliability.

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1 Introduction

Most developing countries have achieved or have targeted universal electricity access, and technical progress has made electric cooking appliances affordable for many developing-country households. However, many of these countries also suffer from a highly unreliable power supply, and air pollution from cooking with solid fuels continues to be a major public health problem in the developing world. We examine the effect of electric power reliability on household air pollution in a sample of households in rural India, most of whom have electric induction stoves. We collected minute-by-minute data on electricity availability, induction stove use, and PM2.5 (a measure of particulate pollution concentration), in 50 households in rural north India for one year. We find that these households have a highly unreliable power supply with frequent and unpredictable outages. Using day-to-day variation for each hour of the day within households that own induction stoves, and controlling for outdoor pollution, we show that electricity availability reduces PM2.5 in kitchens by up to 50 $\mu g/m^3$ (10 to 15%) during morning and evening cooking hours. The effect of induction stove use, when instrumented by electricity availability, is an order of magnitude larger. To put the effect sizes in context, we note that the World Health Organization recently reduced the safe limit for average daily exposure from 25 to 15 $\mu g/m^3$.

Our paper makes two major contributions. First, we contribute to the literature on potential solutions to household air pollution. Most of this literature has been on improved solid fuel stoves and gas, but, as detailed below, improved stoves have largely failed to reduce pollution while gas is limited by issues of cost and scalability in rural areas. Much of the literature measures outcomes other than air pollution, such as stove adoption or firewood use. The few papers that measure air pollution usually do so for just 24 hours or less and are constrained to rely on between-household comparisons (Shupler et al. 2018). Since we have a vastly greater temporal resolution, we can use within-household variation to identify effects of electricity availability. There are very few papers on electric cooking, and these have focused on the effects of electricity access (Barron and Torero 2017; Dendup 2021). The quality of supply varies a great deal, so access by itself is a limited indicator of electricity services (Lee, Miguel, and Wolfram 2020). Instead of access, our data allow us to examine the effect of electricity reliability.

Second, we contribute to the literature on electricity and economic development. Most studies surveyed by Lee, Miguel, and Wolfram (2020) examine outcomes such as income or employment. Taking a different tack, our study suggests that air pollution is an important outcome that should be considered in this literature. This literature has also concentrated on the extensive margin, that is, the effect of electrification[1] while our paper looks at the intensive margin, examining the impact of reliability in electrified households.

Air pollution is the leading killer among all environmental problems worldwide (Cohen et al. 2017),

[1] A notable exception being Allcott, Collard-Wexler, and O'Connell 2016 on the impacts of shortages on industry.

with an impact on life expectancy that resembles that of tobacco smoking and that exceeds all forms of violence by an order of magnitude (Lelieveld et al. 2020). Cooking with solid fuels leads to very high exposure to air pollution in developing countries (Shupler et al. 2018). For example, households are the most important source of ambient air pollution in India (Venkataraman et al. 2018) and the largest contributor to air-pollution related mortality in China (Yun et al. 2020). Moreover, household air pollution remains an intractable problem in all but the richest countries. Decades of efforts to develop improved solid-fuel stoves have had only small impacts due to technological limitations (Venkataraman et al. 2010; Sambandam et al. 2015), low adoption rates (Venkataraman et al. 2010; Mobarak et al. 2012), and infrequent use of the stoves even among adopters (Hanna, Duflo, and Greenstone 2016; Sambandam et al. 2015; Venkataraman et al. 2010). Liquefied Petroleum Gas or LPG, though available in many poor regions, remains expensive given prevailing low incomes.[2] As a result, many people continue to cook with solid fuels and are, therefore, exposed to very high levels of air pollution. Here we examine a third possible source of cooking energy, electricity, and ask whether its reliability reduces air pollution.

Universal electricity access has recently become a major policy goal for developing country governments. Almost concurrently, electric induction stoves have become relatively cheap to buy and operate.[3] Electric cooking, therefore, could become an important part of the solution to the so-far intractable household air pollution problem (Smith 2014; Smith and Sagar 2014; Banerjee et al. 2016; Panagariya and Jain 2016). Dendup (2021) shows that rural electrification in Bhutan led to widespread purchase of electric cooking appliances. Yet the limited success of past clean cooking interventions has naturally engendered skepticism about this potential. Prior experiences have highlighted the deeply cultural aspects of traditional cooking preferences and practices (Pattanayak et al. 2019; Jeuland et al. 2015). Given inequities in electricity access and the unreliability of power supply in many developing countries, it is also unclear if poor households will use electric stoves extensively. Even if they do, it is possible that households will use electricity only to displace other expensive clean fuels like LPG, rather than substituting for dirty solid fuels. Any assessment of the potential of electric cooking to make a substantial dent in household air pollution must address these possibilities. We find that many rural households who own electric induction stoves do in fact use them to cook meals and a substantial fraction of them use induction stoves to cook items that are often thought to be cooked only on open flames. Rural households are more adaptable and less tradition-bound than they are

[2]In India, LPG is sold in metal cylinders marketed by state-owned oil companies at a price that is subsidized by the government. Even the subsidized price of about 500 rupees per cylinder (a quantity that would last 4-6 weeks if used as the primary household cooking fuel) could exceed 10% of monthly income for many rural households in our study site in northern India. The price has risen since 2018-19 when our data was collected

[3]In India, a single-plate stove costs about 1400-2100 rupees (20-30 USD) with a set of compatible utensils costing 700 rupees (10 USD) and up at the time of data collection in 2018-19. Operating costs are a potential concern, but may be zero if electricity is not metered, as was the case in our study area. In places where electricity use is metered, the cost of cooking exclusively with an induction stove is unlikely to exceed 100 rupees per month (about 1.50 USD) for poor households that have no other major electrical appliances, due to widespread use of increasing block pricing with low prices for the first block. Recent field data suggest a growing and meaningful market demand for electric stoves (Pattanayak et al. 2019), including demand for induction stoves in India (Krishnapriya et al. 2021).

sometimes depicted to be.

Most existing research on electric cooking and air pollution relies on between-household comparisons carried out over a single day or two, which makes the findings vulnerable to confounding by unobserved household characteristics that might be related to cooking preferences and behaviors (Gould et al. 2020; Shupler et al. 2018). Since our data contains hundreds of thousands of hourly observations, we can identify the effect of electricity availability on indoor air pollution in households that own electric induction stoves using the within-household variation generated by unpredictable outages. We are able to rule out channels other than induction stove use through which outages can affect indoor air pollution in a subset of the sample households. Using this exclusion restriction to instrument induction stove use by electricity availability, we find that induction stove use reduces PM2.5 by up to 450 $\mu g/m^3$ during cooking hours. Our study area is not untypical for much of northern India, which of course has its own special characteristics. Still, the behaviors and responses that we observe are likely relevant for many developing countries where households face unreliable power supply.

2 Data

The study was conducted in the Sultanpur district of the state of Uttar Pradesh in northern India. When the study began in 2018, only 1% of rural households in Uttar Pradesh had an induction stove (Mani et al. 2018) because this technology had primarily been marketed in urban areas.[4] Dharma Life, a social enterprise that sells induction stoves, gave us access to their customer base. About 70% of their customers in 4 districts of Uttar Pradesh, when contacted by phone, reported that they used their induction stoves for cooking full meals and not just for making tea. We chose Sultanpur district because preliminary visits suggested that it had variable electricity availability and sufficiently many of Dharma Life's customers. We shortlisted villages that had at least 3-4 customers who used induction stoves for cooking full meals. This gave us 50 users in 8 villages. We also monitored 16 nearby households from the same villages that did not possess an induction stove.

We recorded the availability of electricity by installing two voltage monitors for each of the ten power lines that reached sample households. The monitors were provided by the Prayas Energy Group and were in place from 1 September 2018 to 19 September 2019. Reliability is low. During much of the day, there is a better than even chance that the power is out. Outages are more frequent during the day, since electricity demand is higher due to industrial, commercial and cooling demand. (See figure S15 in the Supplementary Materials). The quality of the power supply is also poor: Though the prescribed voltage is 220V, the mean voltage is only 204.6V, with a standard deviation of 27.3. Furthermore, 92%

[4]Percentage obtained from the ACCESS 2018 survey of rural households. Data available at `https://dataverse.harvard.edu/dataverse/IndiaAccess`

of households said that they could not predict the outages before they occurred. This allows us to use exogenous day-to-day variation in electricity supply to help identify the effect of electric cooking on household air pollution.

We measured PM2.5 in all household kitchens in the sample using optical particle sensors developed by the Bergin group at Duke University.[5] We measured ambient PM2.5 with two sensors installed outdoors in each village. We logged use of induction stoves via an ammeter installed in each induction stove owner's home. A member of the research team visited each household once a week while the equipment was in place to upload the data from the SD cards in the air pollution sensors and the ammeters, and to detect and resolve any problems with the equipment. Data from the voltage monitors was transmitted automatically to a server via the mobile phone network. We surveyed households about their cooking habits and electrical appliances in August 2018, in February 2019, and finally in September 2019.

Table 1: No.of households covered in the 3 surveys

Stove Combination		Baseline Survey (August 2018)	Midline Survey (February 2019)	Endline Survey (September 2019)
Induction stove owning households with *Chulha*	Induction, LPG, *Chulha*	39	41	39
	Induction, *Chulha*	3	4	2
Households with only clean stoves	Induction, LPG	8	6	9
Households without induction stoves	*Chulha*, LPG	9	9	12
	Chulha	7	6	3

Notes: All induction-stove-owning households also had either *chulhas* (solid-fuel stoves) or LPG, or both. All households without induction stoves had *chulhas*, among which some had LPG.

While nearly all induction-stove-owners in our sample also had LPG, critically most also had a *chulha*, the traditional mud stove in which firewood or other solid fuels are burnt. Among the other sample households, some used both LPG and a *chulha* while a few used only a *chulha* (Table 1). No household in our sample cooked exclusively with electricity, as would be expected with a highly unreliable power supply. The use of both traditional and modern cooking stoves in the same household, a practice known as "fuel stacking", is widely observed in developing countries (Ruiz-Mercado and Masera 2015). The proportion of relatively rich households in our sample is higher than in rural Sultanpur and Uttar Pradesh (Table S5).

[5]Further details are in Supplementary Materials.

3 Results

Figure 1 shows the percentage of induction-stove-owning households that reported cooking various foods – *rotis* (unleavened bread), lentils, rice, vegetables, other items, and none of the above (NA), using an induction stove (top panel), LPG (middle panel), and a *chulha* or traditional solid fuel stove (bottom panel). Three of the four staple foods – rice, lentils, and vegetables, were cooked more frequently on induction stoves than on LPG stoves or *chulhas*. This frequent use suggests that induction stoves may substitute for the use of smoky *chulhas* and thus reduce pollution. Only *rotis* or unleavened wheat bread, were cooked less frequently on induction stoves. In India, it is frequently asserted that induction stoves are not as versatile as stoves with an open flame, and in particular that *rotis* cannot be cooked on an induction stoves for this reason; our data show this is untrue. However, it does seem that many households prefer to cook *rotis* using LPG or a *chulha* which do have open flames.

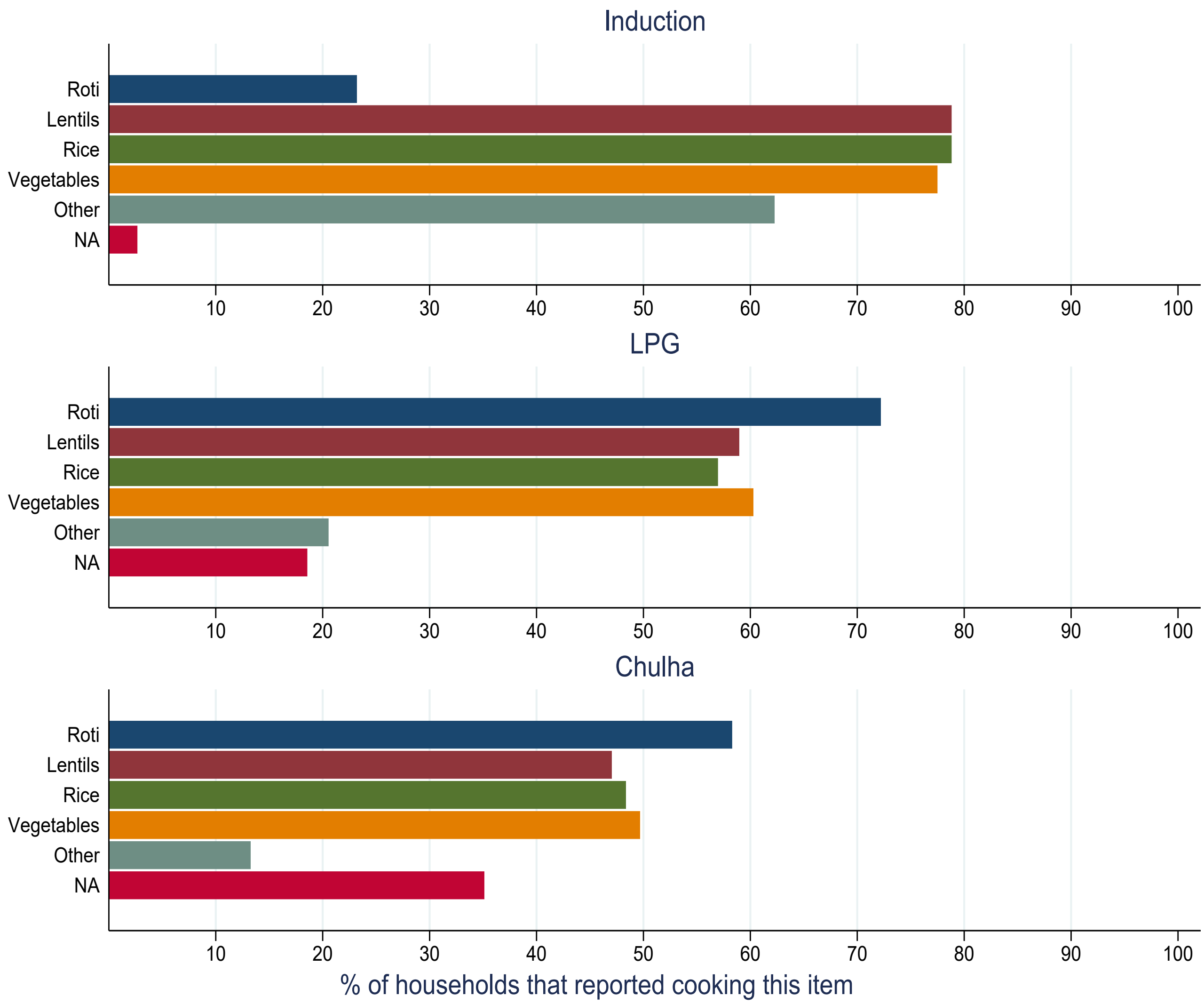

Figure 1: Food items cooked by induction-stove-owning households

Notes: Household survey data show that induction-stove-owning households reported cooking various foods for morning meals on an induction stove (top panel), LPG (middle panel), *chulha* or traditional solid-fuel stove (bottom panel). Data are pooled from the baseline (50 households, August 2018), midline (51 households, February 2019) and endline (50 households, September 2019) surveys. NA stands for None of the Above. In the top panel, the NA responses correspond to 3 households which reported that their induction stoves were under repair. The somewhat larger percentage of NA responses in the middle and bottom panel can be explained by the fact that several households did not possess an LPG stove or a *chulha*. Data for evening meals look similar and are not shown.

Figure 2 shows average kitchen PM2.5 concentrations for each of the three subsamples of households identified in the first column of Table 1, along with outdoor average PM2.5 in the sample villages. Households in the primary subsample, those having both induction stoves and *chulhas* and possibly

LPG as well, have lower kitchen PM2.5 than the subsample of households without induction stoves, especially during the morning and evening cooking hours. (All households surveyed reported that they cooked twice a day, in the morning and the evening.) Households using only 'clean' stoves – induction stoves and LPG, have much lower kitchen PM2.5 concentrations than the other two subsamples that are completely or partially dependent on solid fuels.

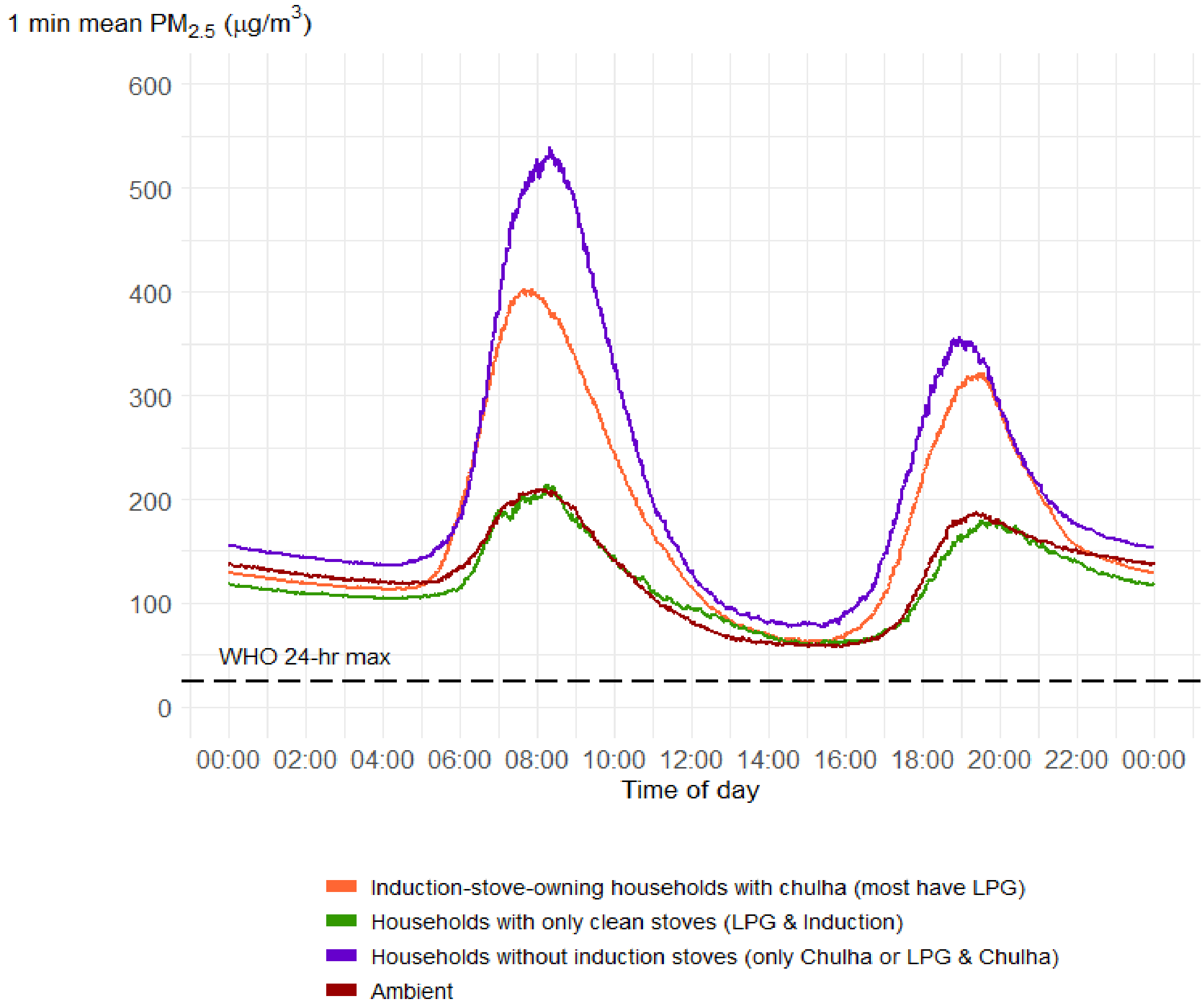

Figure 2: Mean PM2.5 ($\mu g/m^3$) in the sample villages and household kitchens during each minute of the day

Notes: A *chulha* is a traditional solid-fuel stove. PM2.5 ($\mu g/m^3$) for each minute of the day has been averaged over the twelve-month period 1 September 2018 to 19 September 2019. Ambient PM2.5 is averaged over the outdoor sensors in each of the 8 villages, while the others refer to measurements from sensors in kitchens of three different subsamples based on stove ownership. Table 1 shows the number of households within each subsample depicted in the figure. A more detailed plot of average PM2.5 for each stove combination in the second column of Table 1 is shown in Figure S14.

These findings are against a backdrop of extremely high ambient concentration of PM2.5 even during non-cooking hours in the early afternoon and at night. The World Health Organization recommends that the annual average concentration of PM2.5 to which people are exposed should not exceed 5 $\mu g/m^3$, and that the 24-hour average should not exceed 15 $\mu g/m^3$ on any day. The average *outdoor* concentration of PM2.5 in the study villages was 127 $\mu g/m^3$. Furthermore, there are large spikes in kitchen concentrations during cooking hours. In most households and on many days, these levels rise to more than 1000 $\mu g/m^3$ (Figure S13), though Figure 2 shows these spikes in gentler fashion due to averaging. Ambient concentration also rises during cooking hours. This is clearly driven by cooking activity. Indian rural houses are very well-ventilated, so PM2.5 concentrations indoors and outdoors quickly equilibrate by diffusion unless one or the other has an active source. This is why kitchen concentrations closely track the high ambient concentrations during non-cooking hours; it is also why household air pollution that includes short-lived climate pollutants like black carbon has attracted concern from climate scientists (Dasgupta and Ramanathan 2014).

The finding that households with induction stoves have lower PM2.5 concentrations than those without could be due to induction stove use substituting for *chulha* use, thus reducing pollution. It could also be that these households also use more LPG, or cook less than households without induction stoves. In order to remove the effects of such possible confounders, we use the long time dimension of our data to examine how pollution in each household varies from day to day.

To estimate the causal effect of electricity availability on kitchen PM2.5 during morning and evening cooking hours as well as non-cooking times, we aggregate the minute-level data to the hourly frequency. This removes minute-level noise and is better suited to account for the gradual response of PM2.5 concentration in the kitchen to the lighting or dousing of a cooking fire. For each hour, and within each household and month, we compare kitchen PM2.5 across days with varying shares of electricity availability in that hour while controlling for ambient PM2.5. We do this by estimating the following equation using data from the primary subsample of interest, the 45 induction-stove-owning households that also had a *chulha* (and possibly LPG as well).[6] The effects of electricity availability on PM2.5 are given by the coefficients μ_j in the equation

$$Kitchen\_PM2.5_{hljt} = a_{hj} + b_{mj} + c_w + \gamma Ambient\_PM2.5_{ljt} + \sum_{j=0}^{23} \mu_j Elec\_share_{ljt} * hour_j + \epsilon_{hljt} \quad (1)$$

[6] There were 45 unique households that had an induction stove and a solid-fuel stove, and possibly also LPG at some point in the study period. 3 households dropped out about three months into the study and 3 others were recruited to replace them.

where $Kitchen\_PM2.5_{hljt}$ is the average PM2.5 concentration in household h on electricity line l on day t in hour j, a_{hj} is a household-hour fixed effect, b_{mj} is a month-hour fixed effect, c_w is a day-of-the-week fixed effect, $Ambient\_PM2.5_{ljt}$ is the average ambient PM2.5 concentration in the village with electricity line l on day t in hour j (two villages had more than one electrixity line), $Elec\_share_{ljt}$ is the share of time in hour j on day t for which electricity was supplied in line l, $hour_j$ is a dummy variable for hour j, and ϵ_{hljt} is the residual error term for household h on day t in hour j on line l. The household-hour and month-hour fixed effects ensure that the only variation being used to estimate the effect of the electricity share in each hour is day-to-day variation within households and months in that hour of the day. A concern here might be that electricity shares are endogenous if outages happen as a result of induction use. However, as noted above, the proportion of induction stove users in the state of Uttar Pradesh was only 1% in 2018. The villages in our data could have a higher proportion of induction users as a result of the presence of Dharma Life, but the sales of induction stoves even in these villages do not exceed 7% of the total households with the median village sales equal to 0.7% so we can rule out reverse causality [7].

We find that electricity availability reduces kitchen PM2.5 by up to 50 $\mu g/m^3$ during the morning and evening cooking hours (see Figure 3) which is between 10% and 20% of the evening and morning mean peak concentrations seen in Figure 2.

[7] Induction stoves sales data is from Dharma Life until December 2017 and village population data is from Census of India, 2011

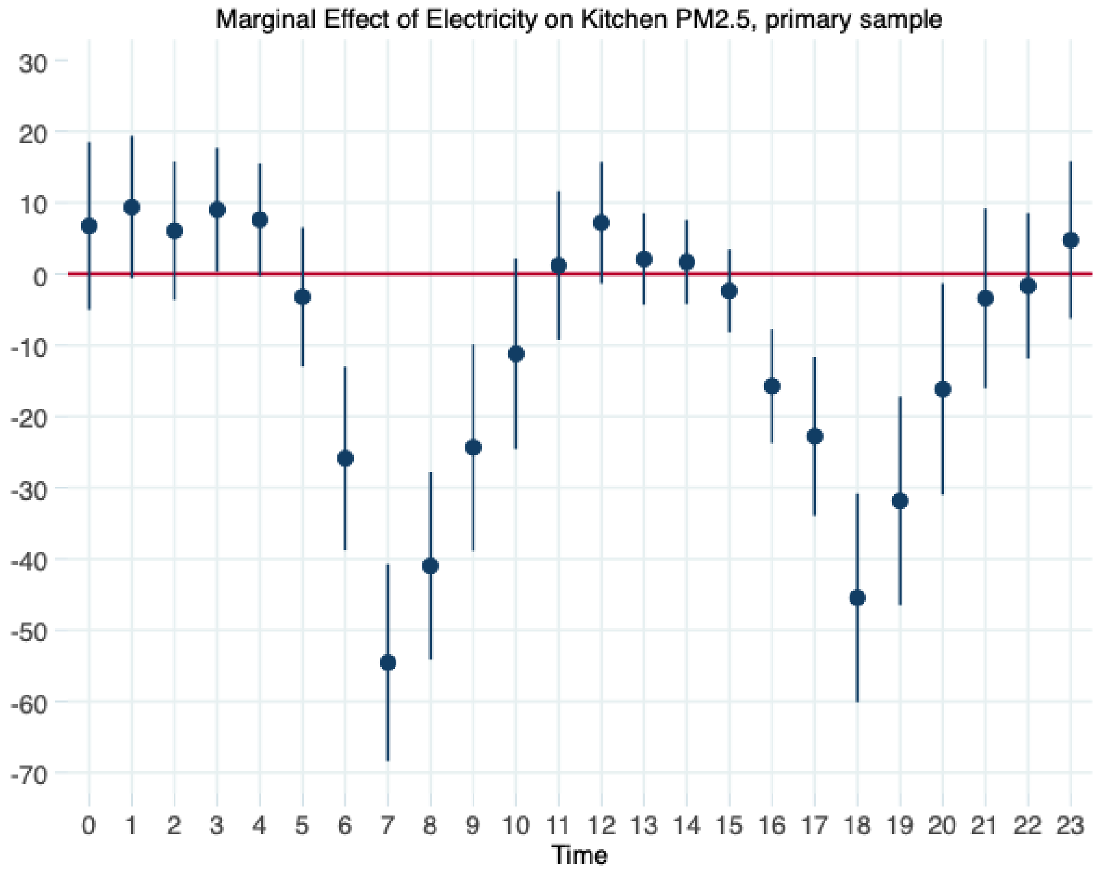

Figure 3: Hour-wise marginal effects of electricity supply on kitchen PM2.5 for induction-stove-owning households with a *chulha* (solid-fuel stove)

Notes: The time labels on the horizontal axis refer to hours beginning with that particular time (eg. 6 refers to 6 AM - 6:59 AM). Plots depict the coefficients μ_j from Equation 1 with 95% confidence intervals computed using Driscoll-Kraay standard errors that are robust to cross-sectional and temporal dependence. Kitchen PM2.5 is the mean concentration in $\mu g/m^3$ in an hour. Electricity is measured as the share of an hour during which the power was not out. The regression uses 228,184 observations on 45 induction-stove-owning households who also had solid-fuel stoves over the one-year time span of the study. Household-hour, month-hour, and day-of-the-week fixed effects are included in the regression (Equation 1).

Since we estimated a large number of coefficients of electricity shares (24), the probability that a few of them are negative under a zero null is much greater than 0.05. To guard against this possibility, we re-estimate Equation 1 using the LASSO estimator (Tibshirani 1996; Ahrens, Hansen, and Schaffer 2020; Chernozhukov et al. 2021) that adds a penalty term – the sum of the absolute values of the regression coefficients – to the usual least-squares minimization problem. LASSO drops variables that fail to contribute much to predicting the dependent variable. Since we want to ensure that our estimates are not confounded by seasonal, hourly, and household-specific variation, we do not penalize these fixed effects in the LASSO procedure. We find that only the electricity shares during morning and evening cooking hours with statistically significant coefficients seen in Figure 3 are selected for inclusion by the LASSO estimator except for the share in hour 20. Ambient PM2.5 was also selected for inclusion. Moreover, the coefficient estimates from the least-squares model after dropping the non-selected coefficients are almost identical to those from the original model (Section S7.1). Our conclusion that electricity availability reduces PM2.5 during morning and evening cooking hours is robust.

The results are also robust to inclusion of electricity shares lagged by one hour (Section S7.2) and by one day (Section S7.3). We noted above that most households said that they could not predict the timing of power outages. This would make it difficult for households to shift the timing of their use of induction stoves and solid-fuel stoves to match power availability. If they were able to do so, then it is possible that even though electricity is associated with reduced pollution at each hour, overall pollution is not reduced by electricity availability, rather its timing is shifted to match electricity supply. If such a substitution across hours or days was actually happening, then the coefficients of electricity shares lagged by an hour or by a day would be positive during cooking hours. However, we find that this is not the case. We can, therefore, conclude that the negative effect of electricity availability on kitchen pollution is, in fact, an aggregate effect, and not just a matter of timing.

A placebo test conducted by running this regression on the subsample of 6 households with only clean stoves (those with induction stoves and LPG but no *chulhas*), showed no negative statistically significant effects of electricity availability on PM2.5 (Sections S7.5). When the LASSO estimator was used on this subsample, none of the electricity shares were selected for inclusion in the model, while ambient PM2.5 was S7.6. This placebo test suggests that the pollution reduction from electricity availability in the primary subsample is largely driven by a reduction in the use of smoke-emitting *chulhas*.

If the dominant channel for the effect of electricity availability on kitchen pollution is indeed the substitution of induction stove use for solid fuel stoves, then we should expect to see little or no effect among households that did not own induction stoves. Running the regression in Equation 1 on the subsample of 15 households without induction stoves, we see that the result depicted in Figure S21 confirms this expectation. Just as we did for the primary subsample, we run the lasso estimator for this subsample. In contrast to the results for the primary subsample, we find that none of the electricity shares are selected. Only ambient PM2.5 is selected for inclusion in the model suggesting that electricity availability does not have much of an effect on kitchen PM2.5 during cooking hours for households that do not own induction stoves.

We now turn to our second major question of policy interest. By how much does induction stove use reduce kitchen PM2.5 in households that also have a *chulha*, controlling for ambient PM2.5? For each hour, and within each household and month, we compare kitchen PM2.5 on days with varying shares of induction stove use in that hour, while controlling for ambient PM2.5. We use electricity availability as an instrument for induction stove use (Equations 2 and 3).

For ease of computation, the following regressions are run separately for each hour j.

$$Kitchen\_PM2.5_{hljt} = a_{hj} + d_{mj} + c_w + \beta_j Ambient\_PM2.5_{hljt} + \gamma_j Induction\_\hat{use}\_share_{hljt} + \epsilon_{hljt} \quad (2)$$

$$Induction\_use\_share_{hljt} = a_{hj} + d_{mj} + c_w + \eta_j Ambient\_PM2.5_{hljt} + \nu_j Elec\_share_{ljt} + \epsilon_{hljt} \quad (3)$$

The identifying assumption being made is that the only channel for the effect of electricity on kitchen pollution after controlling for ambient pollution, is through the use of an induction stove. Due to the ambient control, any other channel must involve either an indoor source that varies with electricity availability, or dispersal of *chulha* smoke that varies with electricity availability.

We consider a comprehensive list of such possibilities. First, we consider fan owners: all households in the sample owned electric table fans that are commonly used for cooling in India during hot weather. None owned exhaust fans. We asked households whether they used their fans in the kitchen during or after cooking hours.[8] Only five households reported doing so, and all five, in response to a follow-up question, said that they did so to clear smoke out of the kitchen, but only in summer and not in winter. We dropped these households from the sample used to estimate Equations 2 and 3. Figure S23 depicts estimates from Equation (1 for households who said they used fans in the kitchen during or after cooking, and those who said they did not. We see that households that use a fan in their kitchen during or after cooking do see larger reductions in kitchen PM2.5 when electricity is available than households that do not. However, we also see that the estimated coefficients for households that do not use fans are very close to those for the entire primary subsample shown in Figure 3. It seems that not enough households use fans to have a sizeable effect on the coefficients.

Second, we consider electric heaters because a *chulha* could be used as a source of warmth in winter to substitute for the heater when the power is out. We excluded two households who own electric heaters from the IV regressions.

Third, we consider backup lighting from a smoky source such as kerosene lamps or candles when the

[8] This question and the questions below on heaters, using a *chulha* for backup lighting, and mosquito deterrence were asked during a follow-up survey in early 2022.

power fails. We classified a household as using a non-polluting backup lighting source if they did not have a kerosene lamp or a candle, *and* if they possessed some form of backup electric lighting such as a solar lamp, or an inverter and battery used to run a light. We excluded the 15 households that did not meet this condition from the IV regressions. Figure S24 shows that in fact, there is very little difference in the marginal effects of electricity availability between households with and without backup electric lighting, except possibly in the hours beginning at 9 and 10 a.m. However, the lighting channel cannot be in play at this time since sunrise occurs by 7 a.m. even in winter.[9]

Fourth, we consider if a *chulha* could be used as a supplementary light source during a power failure, even if it is a poor light source since it is enclosed on at least three sides. If it were kept going longer, it would contribute to increased kitchen pollution during outages. We explicitly asked households if they used their *chulha* as a backup source of lighting, and excluded the 3 households that said they did from the IV regressions.

Fifth, we asked households a series of questions about their use of electric mosquito repellents and 'coils' that emit a little smoke and repel mosquitoes. We excluded from the IV regressions the two households that said they use these methods to repel mosquitoes in the kitchen.

After these exclusions that rule out any channel except induction stove use, we end up with a sample of 22 households with induction stoves and a *chulha* to estimate the IV regressions. As seen in Figure 4, the reductions in kitchen PM2.5 as a result of induction stove use during the morning from 6:00 to 9:00 and evening from 18:00 to 20:00 range from about 220 to 450 $\mu g/m^3$. These are very large effect sizes that are comparable to the average peaks in kitchen pollution during cooking hours that are seen in Figure 2.

First and second-stage coefficient estimates are reported in Section S8. Since the regression for each hour has a single endogenous regressor and is exactly identified, Lee et al. 2021 recommend adjusting the confidence intervals for possibly weak instruments. Since the first-stage (HAC robust) F-statistics during the cooking hours given above are large, if we were to adjust the confidence intervals using their procedure, the ones from 6:00 to 8:00 and at 18:00 would increase by less than 0.5% while the one at 19:00 would increase by less than 5%.[10]

[9] Battery backup does not appear to be sufficient to be used to backup induction stoves. When examining the impact of electricity availability on induction stove use in households with and without battery backup, we find no difference in the coefficients, in a specification with the same fixed effects. Results are available on request.

[10] We show the adjusted standard errors in S8

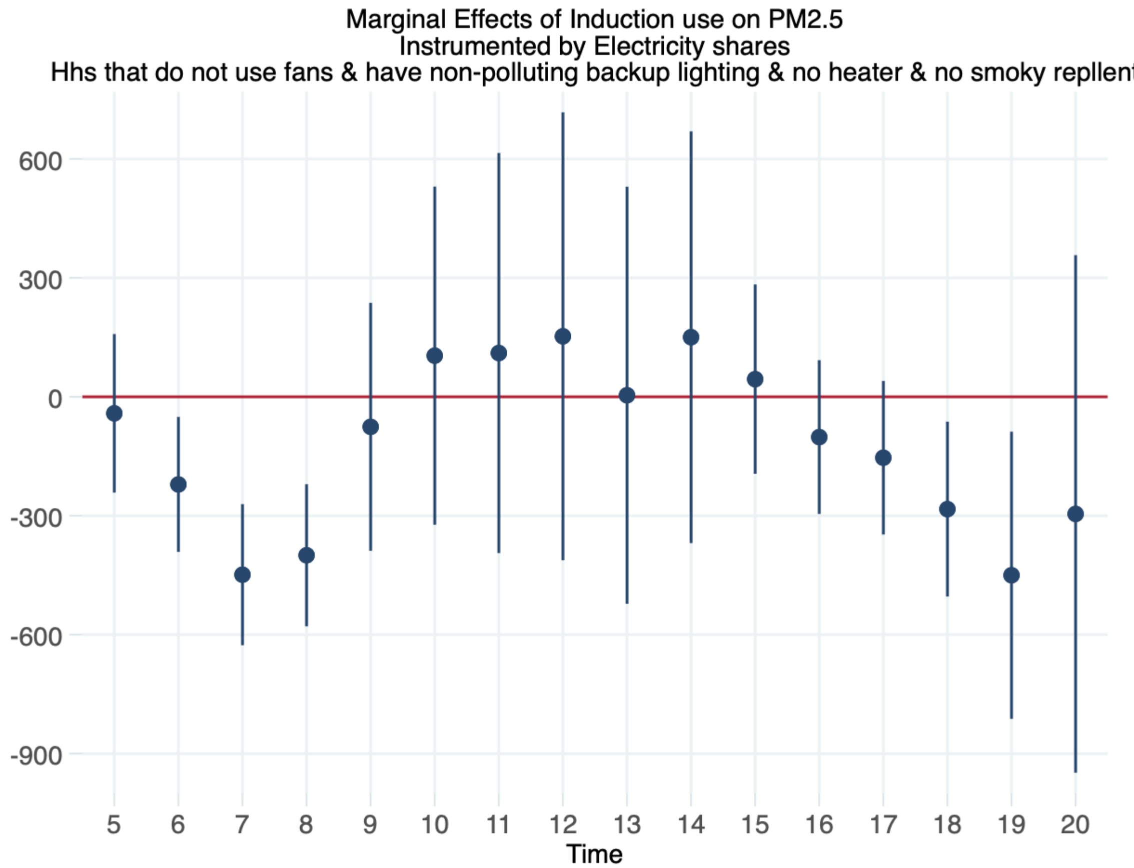

Figure 4: Hour-wise marginal effects of induction stove usage on kitchen PM2.5 for 22 induction-stove-owning households with a *chulha* (solid-fuel stove) who did not use fans, had clean backup power for lighting, did not use their for additional lighting, did not have an electric heater, and did not use a smoky mosquito repellent.

Notes: Plots depict coefficient γ_j from Equation 2. 95% confidence intervals computed using Driscoll-Kraay standard errors that allow for cross-sectional and temporal dependence. The early morning and late night hours are excluded from the figure since some of the first-stage F-statistics are small and/or the effects are not statistically significant, and the confidence intervals are very wide. First and second-stage coefficient estimates are reported in Section S8. Figure S26 plots the first-stage coefficient estimates.

4 Discussion

While electrification has received much attention in the development literature, the role of reliability has been studied less. We have presented new evidence on the effects of electricity reliability at the household level in a developing country. Our study was conducted in a setting of extremely high pollution in a sample of rural household kitchens in northern India that also contribute substantially to ambient pollution. We find that electricity availability substantially reduces air pollution during cooking hours in this setting, and that use of induction stoves greatly reduces air pollution. Thus, improvements in the reliability of electricity together with promotion of electric cooking appear to be promising policies for reducing household and also ambient air pollution.

It is important to note that households in the study area did not pay a per-unit charge for electricity. Instead, they faced a fixed monthly payment, making additional induction stove use essentially free. Increasing the reliability of the grid would certainly impose costs, requiring investment in both infrastructure and enhanced maintenance. To pay for such improvements, the government of UP has been moving in the direction of instituting metering and per-unit charges throughout the study region. So as not to deter households from adopting electric cooking, governments should consider reimbursing the poor for a reasonable portion of their monthly bills, enough to cover cooking and other basic needs.

Our data allow us to quantify the effect of electricity reliability on kitchen pollution at the intensive margin; that is, we examine the effect of greater use of electric induction stoves among households that already possess them. Although Figure 2 suggests an effect at the extensive margin (that is, the effect via more widespread acquisition of induction stoves), to rigorously identify this effect will require data of a different nature. As the market expands, multi-plate stoves and many other electric cooking appliances are likely to be marketed, in addition to the single-plate stoves that are already in use. While there is some research on demand for and supply of electric cooking (Pattanayak et al. 2019; Krishnapriya et al. 2021), these are still very early days for electric cooking in rural India as well as in many other developing countries. Thus, it remains to be seen if the results generalize to other locations. Even so, electric cooking appliances are making inroads in other regions where electricity supply is more reliable, suggesting that this technology can meet rural users' needs (Mani et al. 2018; Pattanayak et al. 2019). Our findings suggest that electricity reliability and electric cooking deserve greater policy attention as a way of tackling the household air pollution crisis in India and other developing countries.

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Author contributions: E.S., M.J, S.K.P, and E.G. designed the study. M.H.B., K.B., and C.N. manufactured air quality sensors and assisted with data processing from them. R.K., U.K., T.V.N., V.C., S.C. deployed and maintained all equipment and collected data. E.S., M.J., E.G., T.R.F., R.K., T.V.N., S.C., V.C., and U.K. analyzed data. E.S., V.C., S.K.P, T.R.F., M.J., and U.K. wrote the paper.
Competing interests: The authors declare no competing interests.
Data and materials availability: All (anonymized) data will be made available in a public database.

Supplementary Materials

Table of Contents

S1 Materials and Methods

The data used in the analysis were obtained using primary surveys and three types of monitoring devices. The devices - air quality sensors, voltage monitors, and ammeters were in place from 1 September 2018 to 19 September 2019.

S1.1 Sample selection and survey

For notational convenience, we define a village as a cluster of households in which a particular representative from Dharma Life (know as a Dharma Life Entrepreneur (DLE)) lived and had sold induction stoves. We have eight such 'villages' in the sample. One of these has households from a single village as defined in the Census of India, six have households from two Census villages, and one has households from four Census villages.

The first survey was conducted in August 2018, a second round in February 2019, and a final round at the conclusion of the study in September 2019. Respondents were asked about their ownership of different kinds of stoves and their preferred stove in each season. The households were also asked to recall the items cooked on each stove and the time at which they cooked their primary meals. A number of questions were asked about their electricity supply. Households were paid a monthly amount of 200 rupees (2.69 USD) for their permission to install monitors in their homes, to not switch them off, and for allowing our field staff to collect data from the devices periodically. Respondents were also paid 100 rupees (1.35 USD) for participation in each survey.

S1.2 Voltage monitors

The data on electricity supply were collected using voltage monitors (Figure S1 A) provided to us by the Prayas Energy Group (https://www.prayaspune.org/peg/). These monitors record voltage every minute and transmit it via the mobile phone network to Prayas's server. Monitors were placed on a total of 10 electricity lines, as 2 out of the 8 villages had more than one electricity line.

Poor connectivity to the mobile network in the villages led to some missing data (see Table S1), a problem that was reduced by installing a primary and backup monitor in 2 households in each village. We use the minute-level records to code the presence of electricity, with an indicator equal to 1 if the reading in a given minute is greater than 100 volts, and 0 otherwise.

Table S1: No. of non-missing observations (in millions) from minute-level electricity data used in Figure S15

Voltage Monitor	Sep-Nov 2018	Nov-Mar 2019	Apr-June 2019	Jul-Sep 2019
Non-Missing Observations	1.04 (95.5 %)	1.93 (98.4%)	1.31 (99.6%)	1.12 (96.1%)

Notes: The parentheses show these numbers as percentages of the total number of observations we would have if all voltage monitors functioned properly for every minute from 1 Sep 2018 to 19 Sep 2019.

S1.3 Air quality sensors

The air quality sensors (Figure S1 B) were developed by the Bergin group at Duke University (http://bergin.pratt.duke.edu/) and have been used previously in other relatively polluted environments (Barkjohn et al. 2019; Zheng et al. 2018). These sensors capture minute-level PM2.5 concentration, and were installed in the primary cooking space used by every study household about 1.5 to 2 meters above the ground. Each sensor was powered by a 6 V rechargeable lead acid battery, which was connected to a normal power source all through the day. Households were instructed not to disconnect the battery.

To capture ambient pollution levels, two sensors were installed in open spaces within the premises of some households in each village. To minimize data loss on ambient pollution, we inspected the time series from each ambient sensor and used the one that had less missing data for our regression analysis. Gaps in the data from the chosen ambient sensor were filled in by data from the other ambient sensor, if it was found to be recording data over the same period.

A B C

Figure S1: Devices that were deployed on the field.

Notes: Figure A is the electricity supply monitor deployed in the field. These were obtained from the Prayas Energy Group. Figure B shows the air quality sensor developed in the Bergin lab at Duke University. Figure C represents the induction stove monitors that were developed by a local manufacturer in Delhi, India.

The sensors were intended to be on at all times, but gaps nonetheless occurred during periods with frequent or long duration outages, when the lead acid battery became drained. When the batteries were drained to the extent that they could no longer power the air quality sensor, the sensors would stop recording data (even after the batteries got recharged) until our field assistant restarted the sensor. The sensor batteries would not recharge if the voltage dropped much below the prescribed standard of 220V, and this accounts for most of the data losses. Table S2 records the number of non-missing observations in the sensor data for different types of households. Since about 37% of the kitchen sensor data for induction-stove-owning households is missing, it is important to check if this could bias our results.

One possibility is that data from air quality sensors is missing more often following long-duration outages, and households are also reluctant to stop using *chulhas* after such outages. This would tend to over-estimate the negative effect of electricity availability on air pollution in Equation 1. However, as seen in Figure S2, only a very small fraction of outages are greater than 36 hours, which is what it would take to drain the sensor batteries. Therefore, this source of bias is negligible.

Table S2: No. of non-missing observations (in millions) from minute-level PM2.5 data used in Figure 2.

Sensor Type	Sep-Nov 2018	Nov-Mar 2019	Apr-June 2019	Jul-Sep 2019
Induction-stove-owning households	2.86 (52.3%)	7.93 (79.4%)	4.49 (67.2%)	2.58 (43.4%)
Households without induction stoves	0.90 (51.5%)	2.59 (82.7%)	1.07 (54.5%)	0.52 (30%)
Ambient sensors	0.72 (81.8%)	1.47 (94%)	1.00 (95.2%)	0.64 (69.1%)

Notes: Non-missing observations as a percentage of the total that would have been observed if all air quality sensors were functioning for every minute from 1 Sep 2018 to 19 Sep 2019 are given in parentheses.

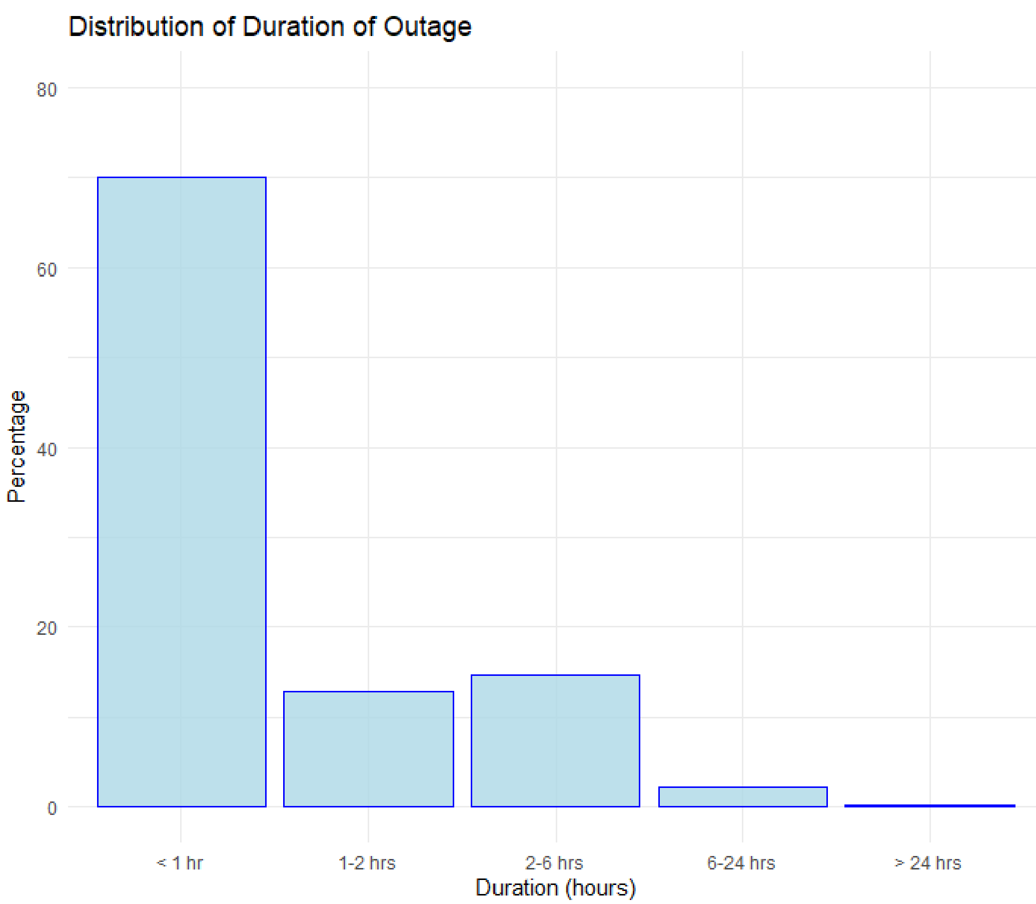

Figure S2: Distribution of duration of outages

Figure S3 shows distributions of voltages conditional on sensor data being missing and non-missing separately. It can be seen that a greater share of voltages lie in the lower range when PM2.5 is missing. This is in line with our expectations since low voltage electricity was one of the main reasons for sensor batteries not getting recharged, and for RTC resets. If low-voltage electricity leads to less use of induction stoves than near-normal voltage electricity, then the estimated effects of electricity in Equation 1 would apply to normal-voltage electricity but perhaps not to low-voltage electricity. We examine this by running a modified version of Equation 1 in which the share of the period electricity is available is replaced by two variables, the share of the period low-voltage electricity is available, and the share of the period that near-normal voltage electricity is available. Figure S25 shows that the effect sizes during cooking hours appear to be a little smaller for low-voltage electricity and about the same as in the original specifications for near-normal voltage electricity.

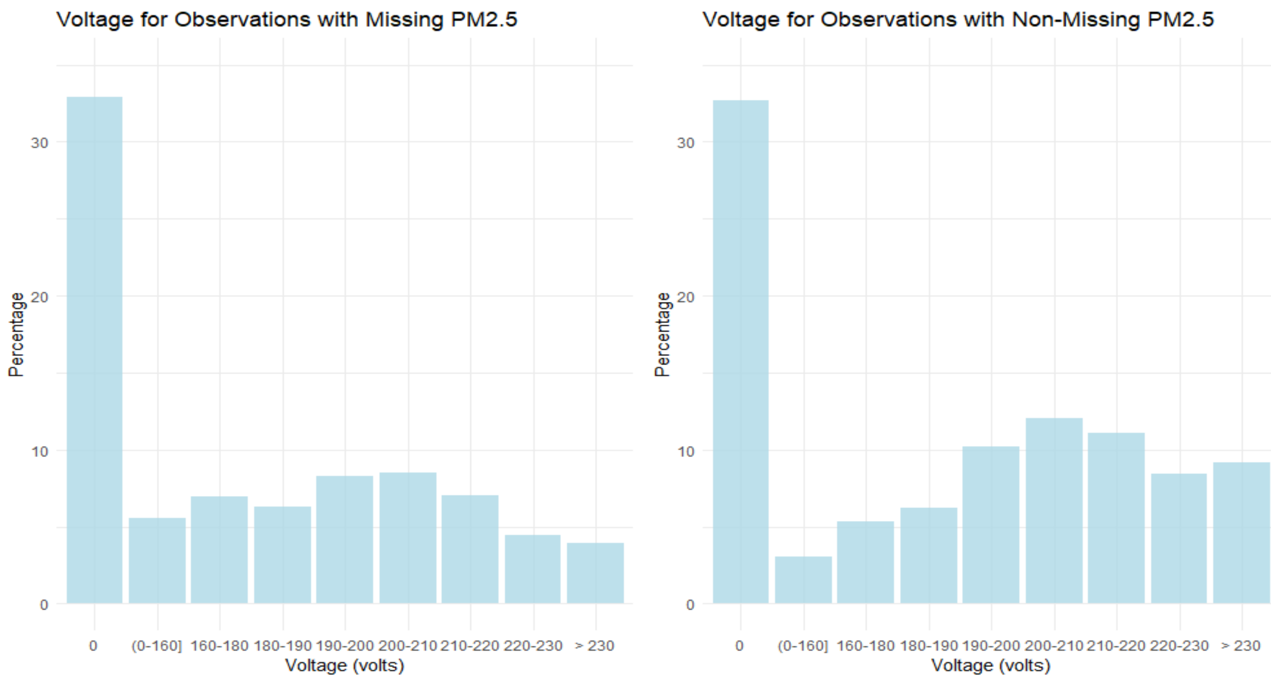

Figure S3: Voltage Distribution when PM2.5 is missing (left) and non-missing (right)

Two lesser causes of data losses were resets of the real-time clocks (RTCs) on the sensors, and particulate matter getting stuck in the intake to the light-scattering chamber. These events are likely to be unrelated to induction stove use in addition to being less frequent, and are, therefore, not likely to bias our regression results. The real time clock (RTC) in the air quality sensors sometimes spontaneously reset to 1/1/2000. This could happen once or multiple times between two successive data-collection visits. However, most of this data was recovered by mapping the incorrect times to the times at which the data was collected (recorded by our field assistant).[11]

[11]Occasionally, the RTC (real-time clock) had to be corrected by reprogramming the Arduino board in the sensor. In

If particulate matter gets stuck in the chamber where light-scattering by PM occurs, it can result in relatively stable but erroneous concentrations of PM2.5 readings. Depending on which component of the sensor is being obscured, these readings could be abnormally high or abnormally low. In order to overcome this problem and minimize data loss, compressed air was routinely used to clean the sensors. Outliers arising due to the aforementioned problem were identified by inspecting the plots of the sensor data and affected observations were dropped. These constituted about 15.7% of missing kitchen sensor data.

Data from the air quality sensors were adjusted to account for under-statement of PM2.5 at high levels ($> 200\mu g/m^3$) and over-statement at low levels of PM2.5. We contracted with the National Physical Laboratory (NPL), Delhi to calibrate the sensors in India. All the optical sensors were co-located with a Beta attenuation monitoring (BAM) sensor in ambient conditions (concentrations ranging between $50\mu g/m^3$-$200\mu g/m^3$) in the NPL lab in Delhi to simply check if there were any obvious defects in any sensors. A few malfunctioning sensors were replaced with new sensors. All sensors tracked BAM readings quite well and 5 were chosen randomly to act as reference sensors for our calibration process. Next, data were recorded for all sensors against two of our reference sensors at high PM2.5 concentrations ($> 500\mu g/m^3$) generated using incense sticks as well as low concentrations in an indoor laboratory ($30\mu g/m^3$-$50\mu g/m^3$). Sensors that did not show any defects were then deployed in the field.

In our final calibration step, we recorded PM2.5 readings from one of our reference sensors against an Aerodynamic Particle Sizer (model TSI 3321). Data from this process was used to fit a calibration equation which was then used to adjust data from all sensors in the field (See Figure S4). This adjustment is very close to one computed earlier in the Bergin lab at Duke University during a similar and independent calibration exercise which used a TSI Dustrak instrument as a reference sensor.

In February 2019, we examined whether there was any drift in our air quality sensor readings that had been installed in the sample households' kitchens for six months. We chose 2 out of the 5 reference sensors and co-located them with one kitchen sensor in each village for about 24 hours. As can be seen in Figures S5 - S12, the kitchen sensors tracked our reference sensors well and we did not find any evidence of a drift in the readings. The reference sensor in village 2 got stuck after about 3.5 hours of the start of the co-location and showed unreasonably high concentrations, (the issue mentioned above) these data were dropped.

addition, the coin battery in the clock had to be replaced after a couple of months to avoid multiple resets.

S1.3.1 Calibration Equation

$$APS\_PM2.5_t = \beta_1 Sensor\_PM2.5_t + \beta_2(Sensor\_PM2.5_t - 200) * D_t + \epsilon_t \tag{S1}$$

where $APS\_PM2.5_t$ is the PM2.5 value recorded by the Aerodynamic Particle Sizer (APS) at time t,
$Sensor\_PM2.5_t$ is the PM2.5 value recorded by our air quality sensor at time t,
D_t is a dummy variable that takes value 0 when PM2.5 $\leq$ 200 and 1 when PM2.5 $>$ 200

The estimated coefficients are displayed in the following table. Intercepts have been forced to zero.

Table S3: Calibration Equation

	Slope Coefficient
Sensor_PM2.5	0.8572***
	(0.0839)
(Sensor_PM2.5 - 200)D	1.5950***
	(0.0599)
Obs	107
R-Sq	0.982

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses

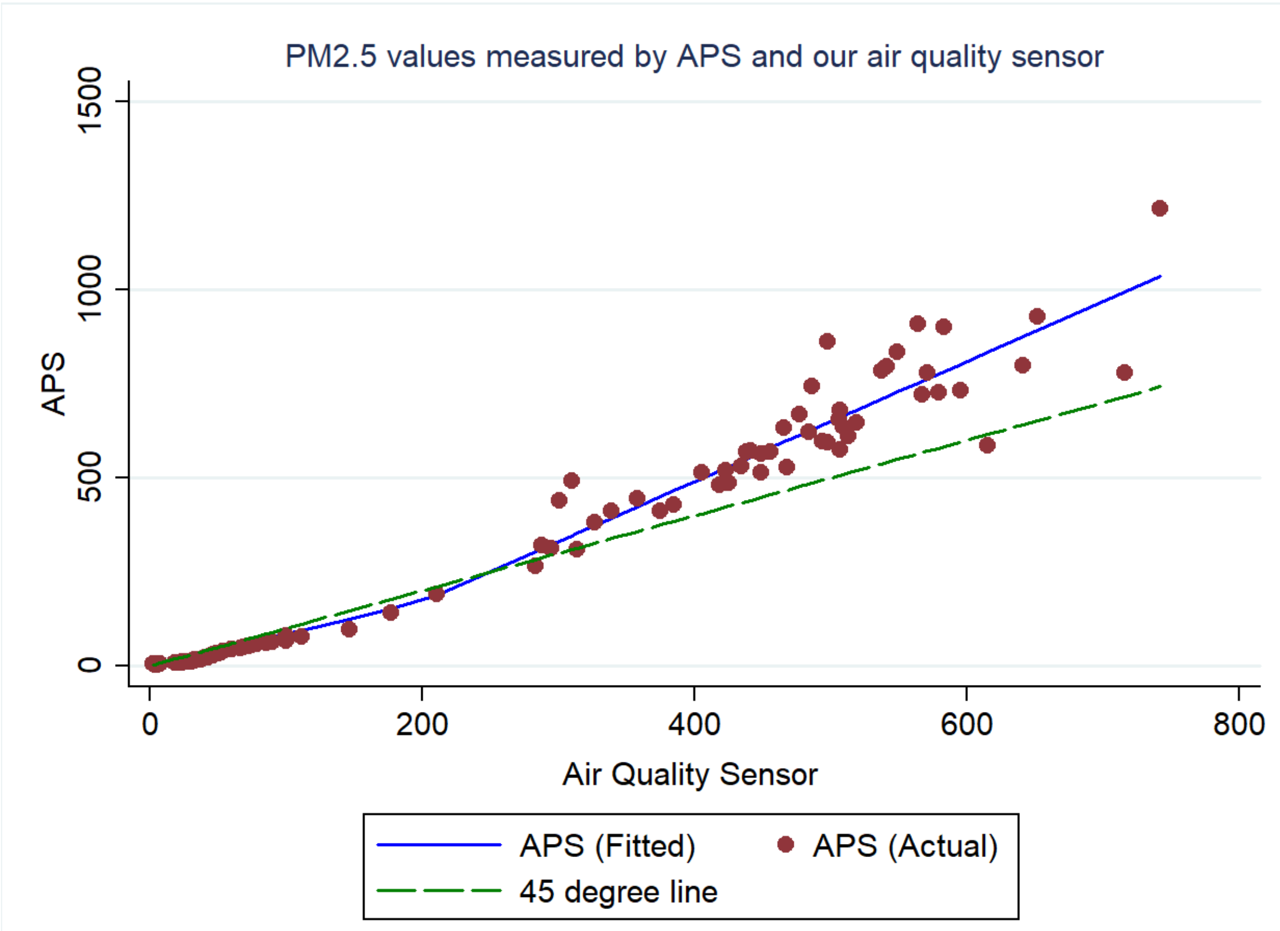

Figure S4: Piece wise regression used to estimate the calibration equation for the air quality sensors deployed in the field

Notes: Our sensor was tested against an Aerodynamic Particle Sizer (APS) and it was noted that our sensors underestimated pollution at higher concentrations and overestimated at lower concentrations of pollution. The relevant adjustments were made to the sensor readings.

S1.3.2 Co-location plots: One Sensor from each village was co-located with a reference sensor

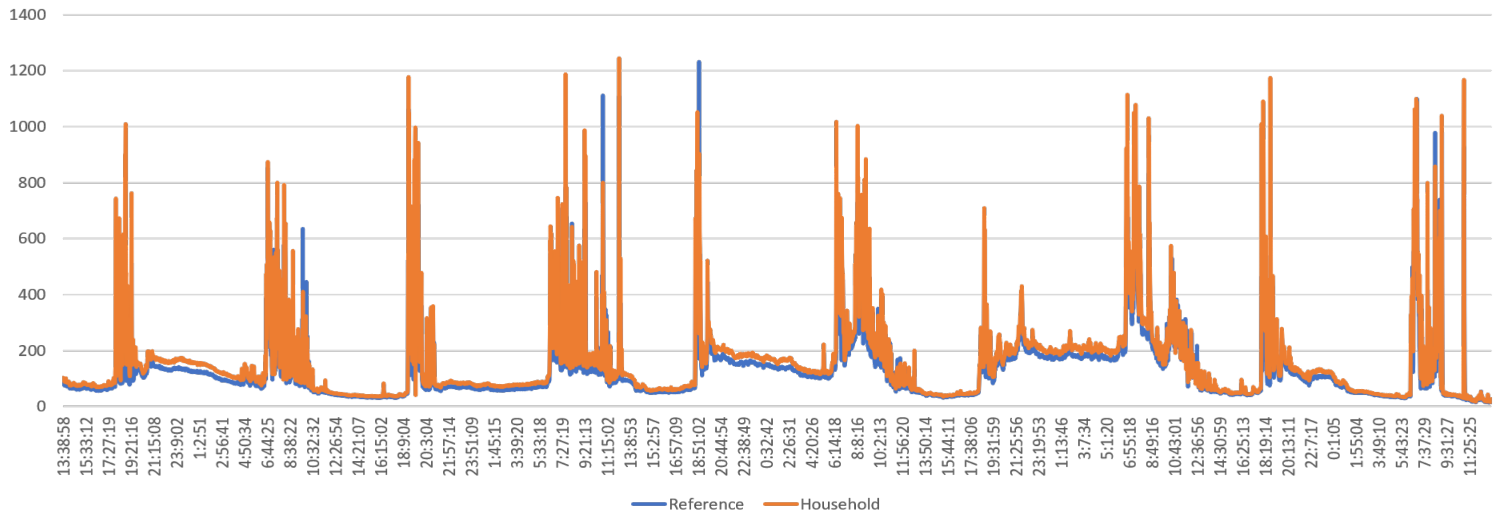

Figure S5: Village 1 : Reference Sensor - 88i, Household Sensor - 87i

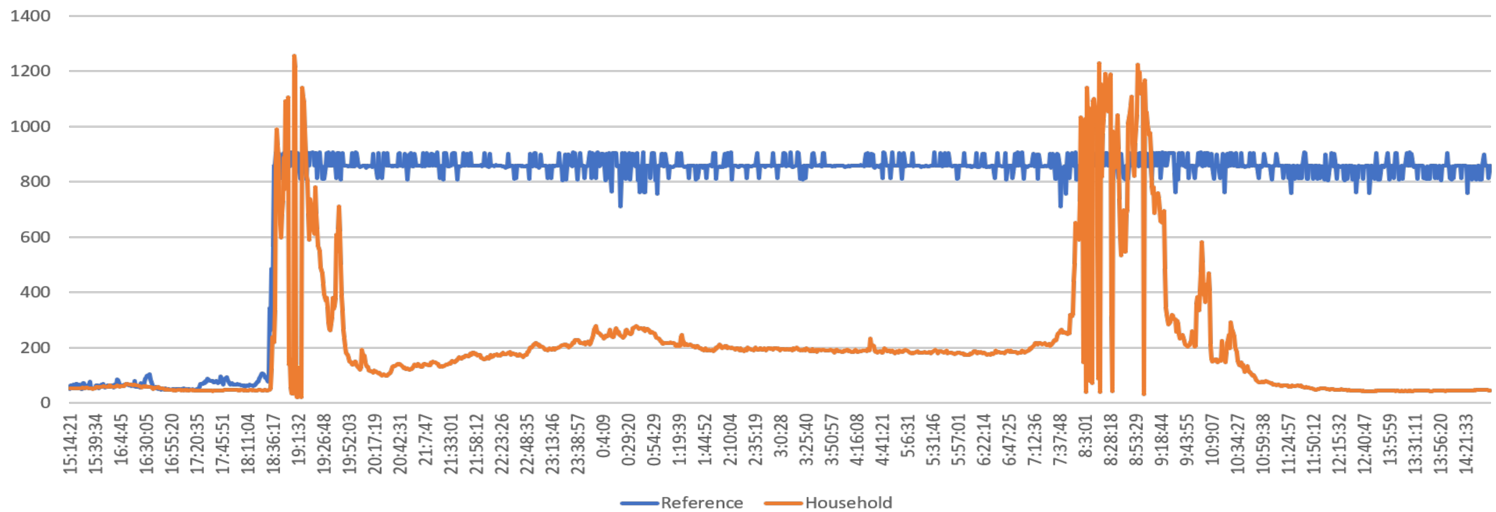

Figure S6: Village 2 : Reference Sensor - 37i, Household Sensor - 31i (Note: The stuck PM2.5 concentrations have been removed before conducting analysis)

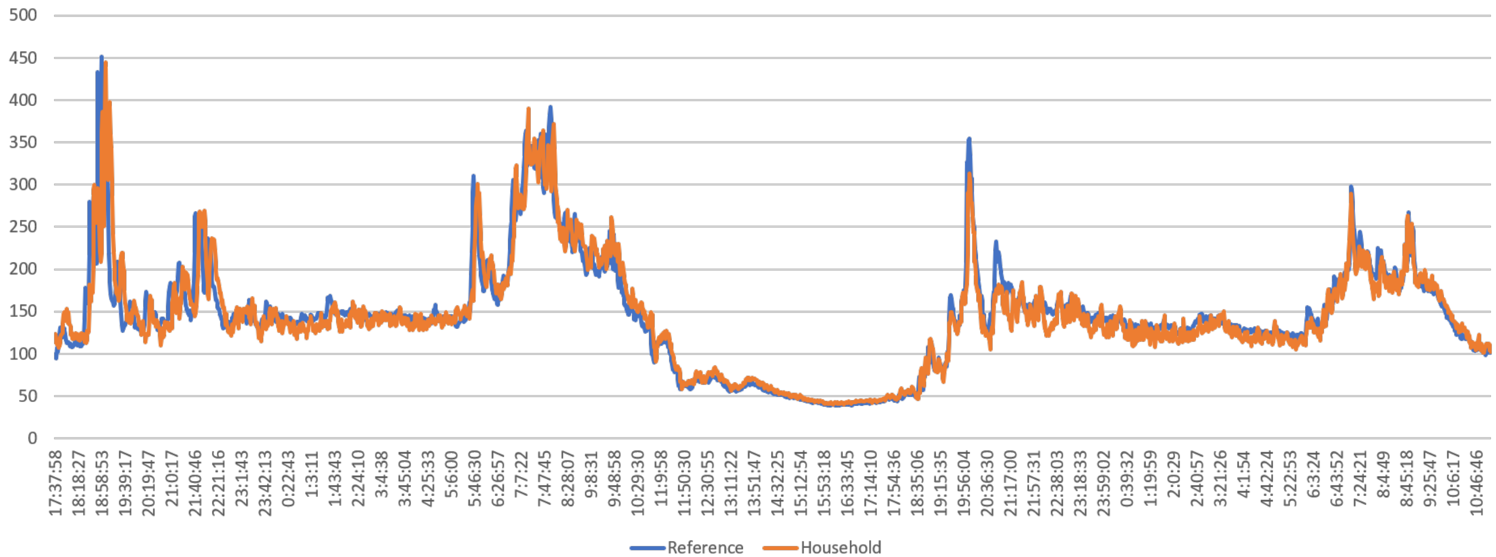

Figure S7: Village 3 : Reference Sensor - 88i, Household Sensor - 26i

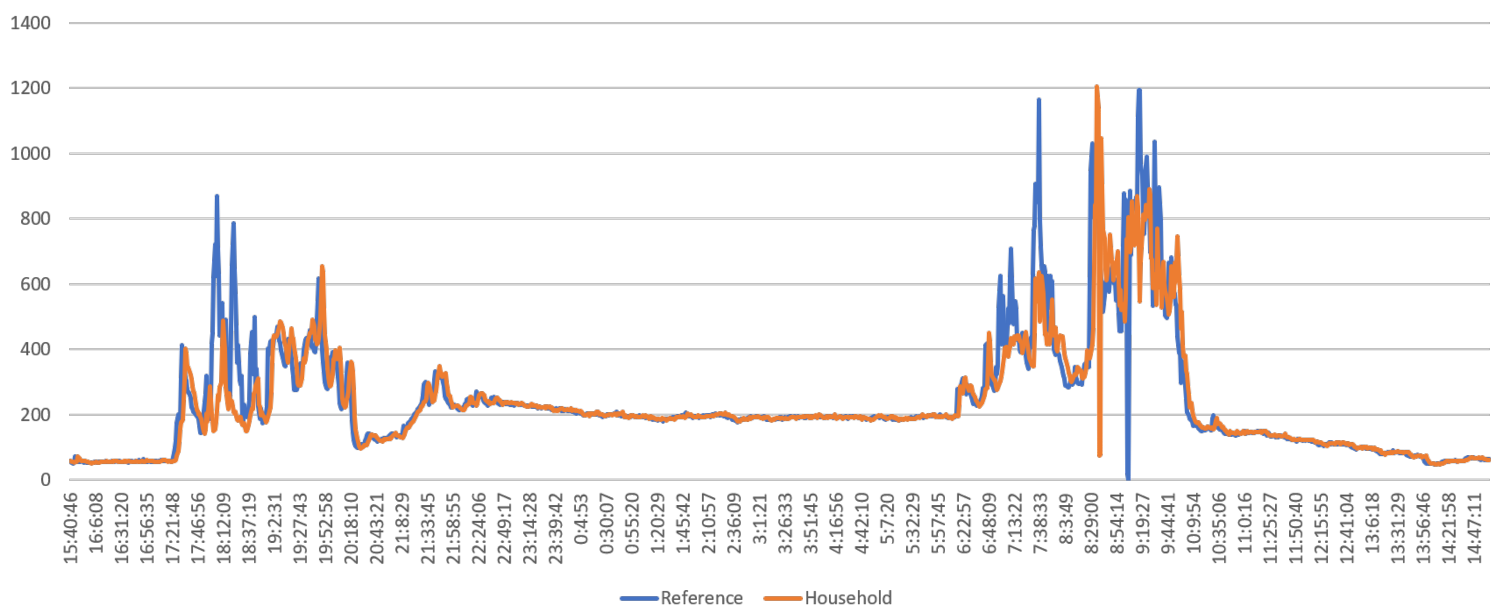

Figure S8: Village 4 : Reference Sensor - 37i, Household Sensor - 77i

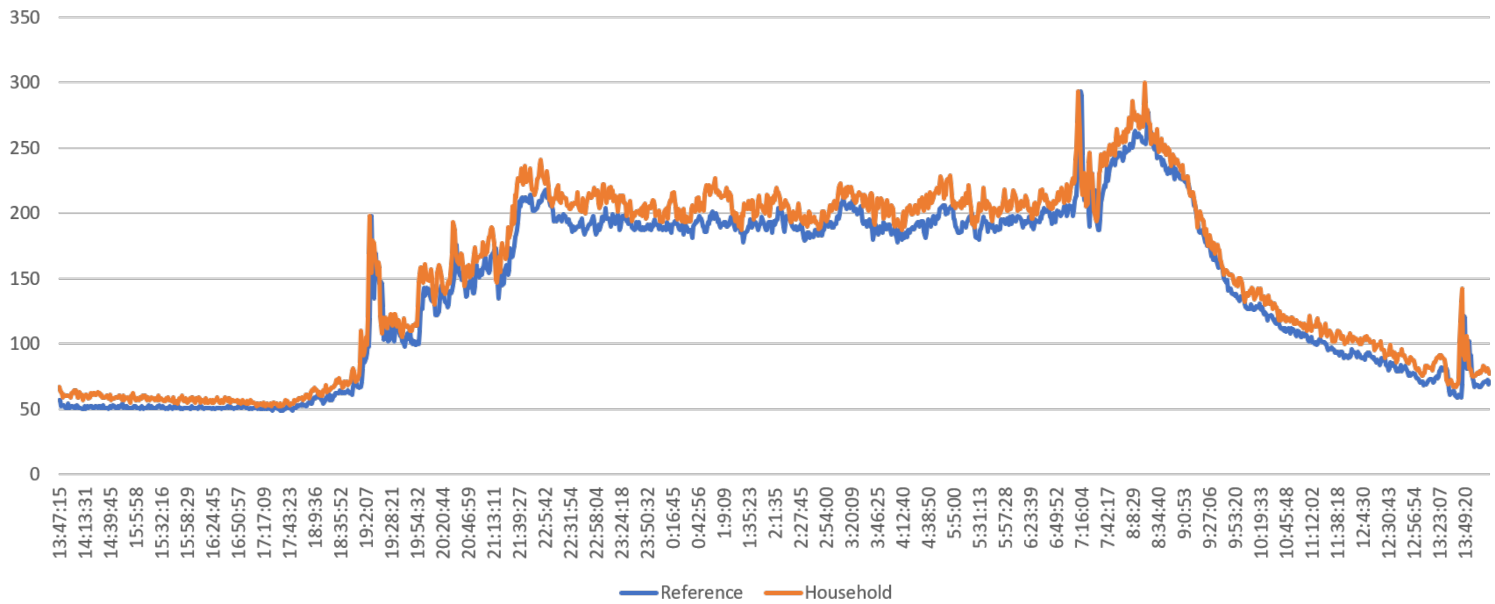

Figure S9: Village 5 : Reference Sensor - 88i, Household Sensor - 25i

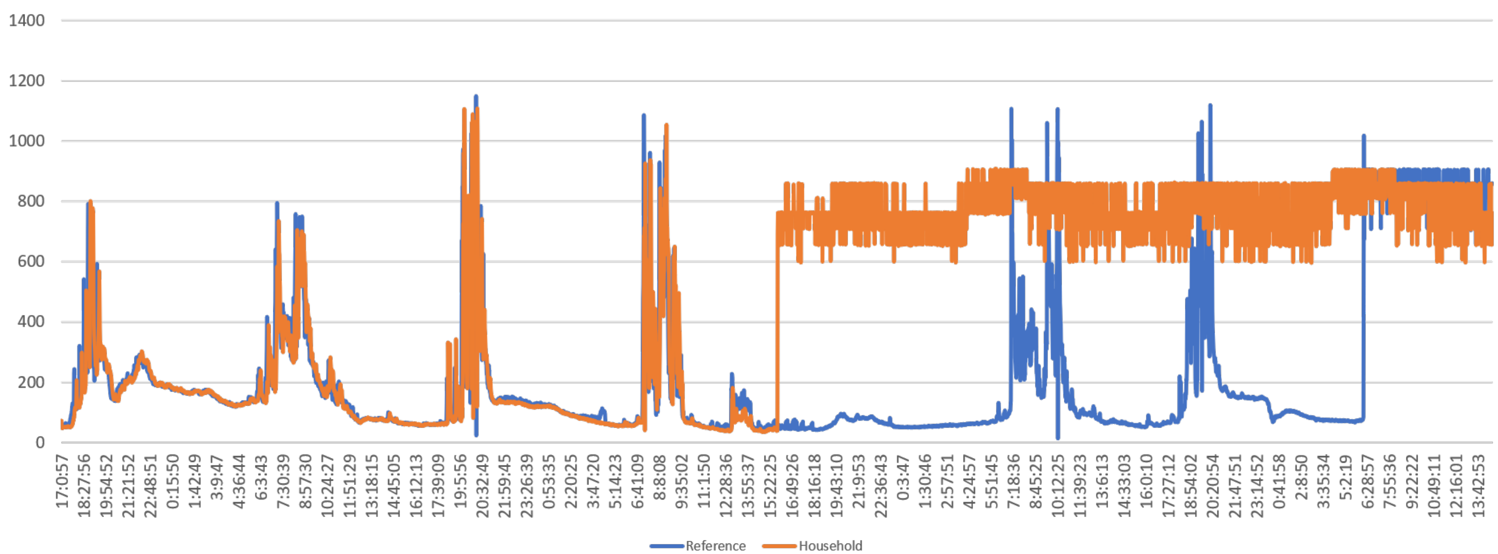

Figure S10: Village 6 : Reference Sensor - 37i, Household Sensor - 73i (Note: The stuck PM2.5 concentrations have been removed before conducting analysis)

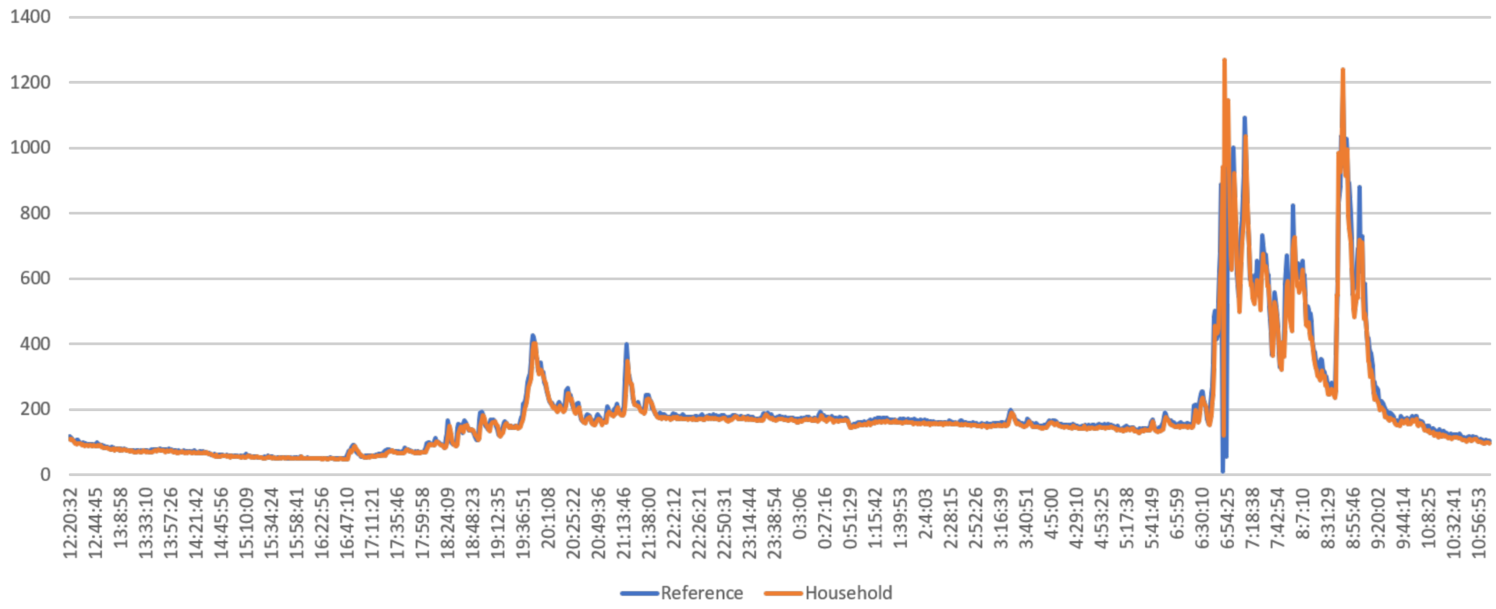

Figure S11: Village 7 : Reference Sensor - 88i, Household Sensor - 30i

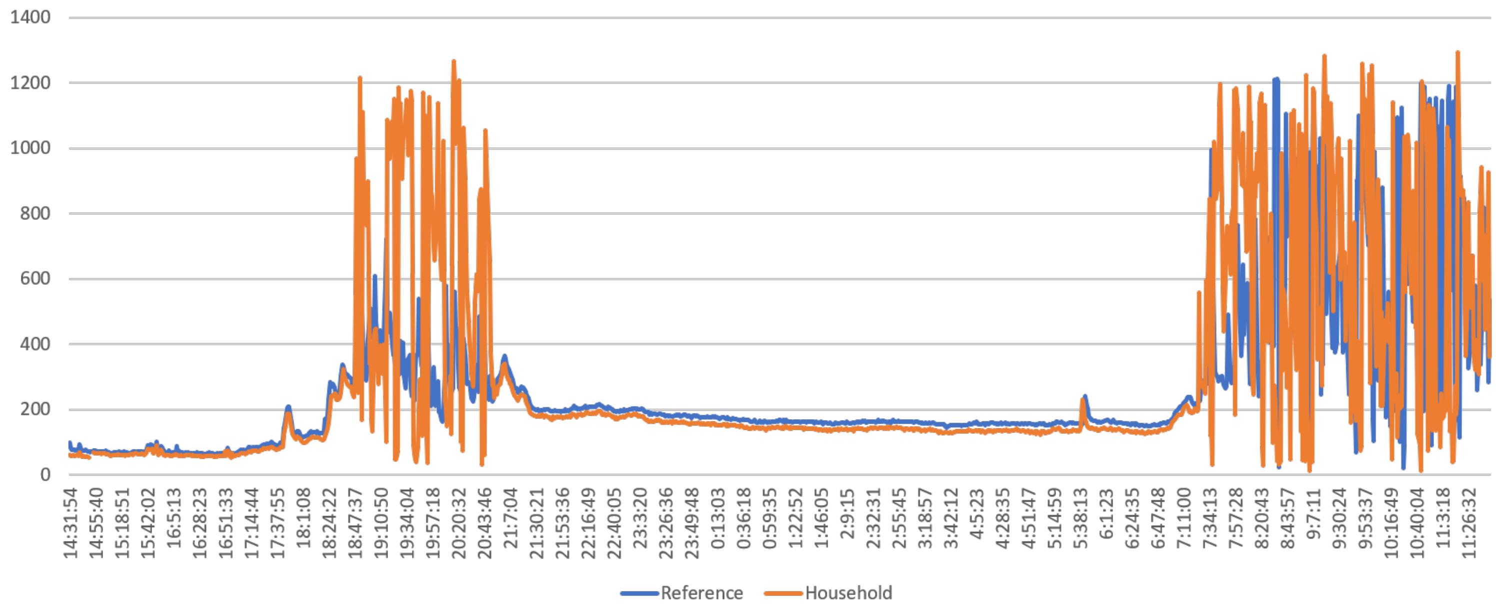

Figure S12: Village 8 : Reference Sensor - 37i, Household Sensor - 85i

S1.4 Ammeters

To measure induction stove use, we used ammeters with a data logger built to our specifications by a manufacturer in Mumbai, India (Figure S1 C). Each ammeter was connected to an induction stove on the line connecting the stove to the wall socket. It recorded a proxy for current flowing through the circuit whenever the induction stove was turned on, at minute-by-minute intervals. These data were stored on an SD card and collected by our field assistant on a weekly basis. No data were recorded when the stove was not being used.

The real-time clocks (RTCs) in the ammeters were subject to drift (a difference in device time and actual time), an issue which was first noted at the end of December 2018. This problem may have been caused by the low quality of electricity supply. The devices were removed for much of January for re-engineering to fix this problem, so ammeter data for these days were not obtained. Thereafter, in March 2019, the devices were modified again to allow our field assistant to update the time in the device if a drift was found during a data collection visit.[12] Where feasible, data were corrected to account for observed drifts in the RTCs. We corrected for drifts that arose prior to December 2018, assuming that the drifts occurred at a constant rate between the time the RTCs were reset for the first time on July 05, 2018, and the time of record of the discrepancy in January 2019. There were 5 ammeters in which the clocks had drifted by more than 3 hours. Data from these were dropped. Drifts observed after March 2019 were corrected using the same constant drift rate assumption and data for periods with drifts greater than or equal to 3 hours were dropped. These corrections were based on the drifts recorded by our field assistant during data collection visits. Drifts could be recorded only when the devices did not suffer from SD card issues and the RTC could be updated. Since problems with SD cards worsened over time, there were a number of devices with no drift records at the end of the study period. Such ammeters were assumed to have no drift in September 2019 if the last observed drift was less than an hour. If the last observed drift exceeded an hour, the subsequent data were dropped.

The SD cards in the ammeters sometimes had errors that prevented recording of data, evidently due to the card socket's exposure to cooking smoke. This problem got worse over time and is the major cause of missing data. To deal with this issue, we reformatted or replaced affected SD cards during data collection visits. Table S4 shows the number of non-missing observations in the induction stove usage data.

[12] We are grateful to Vijay Rao for technical help with re-engineering and other ammeter issues.

Table S4: No. of non-missing observations (in millions) from minute-level induction stove usage data

Ammeter	Sep-Nov 2018	Nov-Mar 2019	Apr-June 2019	Jul-Sep 2019
Non-Missing Observations	4.56 (83.4%)	6.22 (62.3%)	4.39 (65.7%)	2.68 (45%)

Notes: The parentheses show these numbers as percentages of the total number of observations that would have been obtained if all ammeters functioned properly for every minute from 1 Sep 2018 to 19 Sep 2019.

S2 Sample description : Asset ownership

Table S5: Household Ownership of Assets

	Sultanpur (Rural)	Survey	UP (Rural)
Car/Truck	0.0180	0.136	0.0200
Computer	0.0360	0.166	0.0270
Cots	0.986	1	0.982
Livestock	0.639	0.818	0.603
Bicycle	0.888	0.878	0.765
Electric Fan	0.609	1	0.510
Refrigerator	0.0680	0.348	0.102
Kachcha Floor	0.870	0.500	0.757
Kachcha Roof	0.186	0.0600	0.153
Kachcha Walls	0.368	0.242	0.192
Cellular Phone	0.920	1	0.899
Mosquito Nets	0.367	0.818	0.451
Motorcycle	0.294	0.712	0.282
Land	0.725	0.939	0.667
Sewing Machine	0.273	0.606	0.260
Television	0.358	0.666	0.328
Tractor	0.0410	0.151	0.0490
Washing Machine	0.0180	0.106	0.0480
Water Pump	0.186	0.378	0.195
Sample Size	837	66	55,850

Note: The table shows the proportion of households that own one or more of the identified durable assets from the latest round of the National Family Health Survey (NFHS 2015-16) and our own baseline survey data. Columns 1 and 3 represent data from respective cuts in NFHS, and column 2 presents data from our household survey of 8 villages in Sultanpur. On average, households in our study are more likely to own these durable assets than the samples from rural Sultanpur and rural UP as reported in NFHS 2015-16. This partly reflects economic growth (19%) in UP over the three years from 2015 to 2018. Note that *Kachcha* building materials refer to mud, thatch, or other locally-available (but lower-quality) materials.

Table S6: Ownership of Assets by Household Type

	Induction-stove-owning households	Households without induction stoves
Car/Truck	0.18	0
Computer	0.20	0.0625
Cots	1	1
Livestock	0.78	0.9375
Bicycle	0.84	1
Electric Fan	1	1
Refrigerator	0.4	0.1875
Kachcha Floor	0.5	0.5
Kachcha Roof	0.08	0
Kachcha Walls	0.24	0.25
Cellular Phone	1	1
Mosquito Nets	0.88	0.625
Motorcycle	0.72	0.6875
Land	0.94	0.9375
Sewing Machine	0.68	0.375
Television	0.76	0.375
Tractor	0.16	0.125
Washing Machine	0.14	0
Water Pump	0.4	0.3125
Sample Size	50	16

Note: The table shows the proportion of households that own one or more of the identified durable assets based on our baseline survey in 8 villages in Sultanpur. Column 1 represents households that reported owning induction stoves at the time of the baseline survey, and column 2 represents households that do not report induction stove ownership.

S3 Kitchen and ambient PM2.5 concentrations in one household on one day

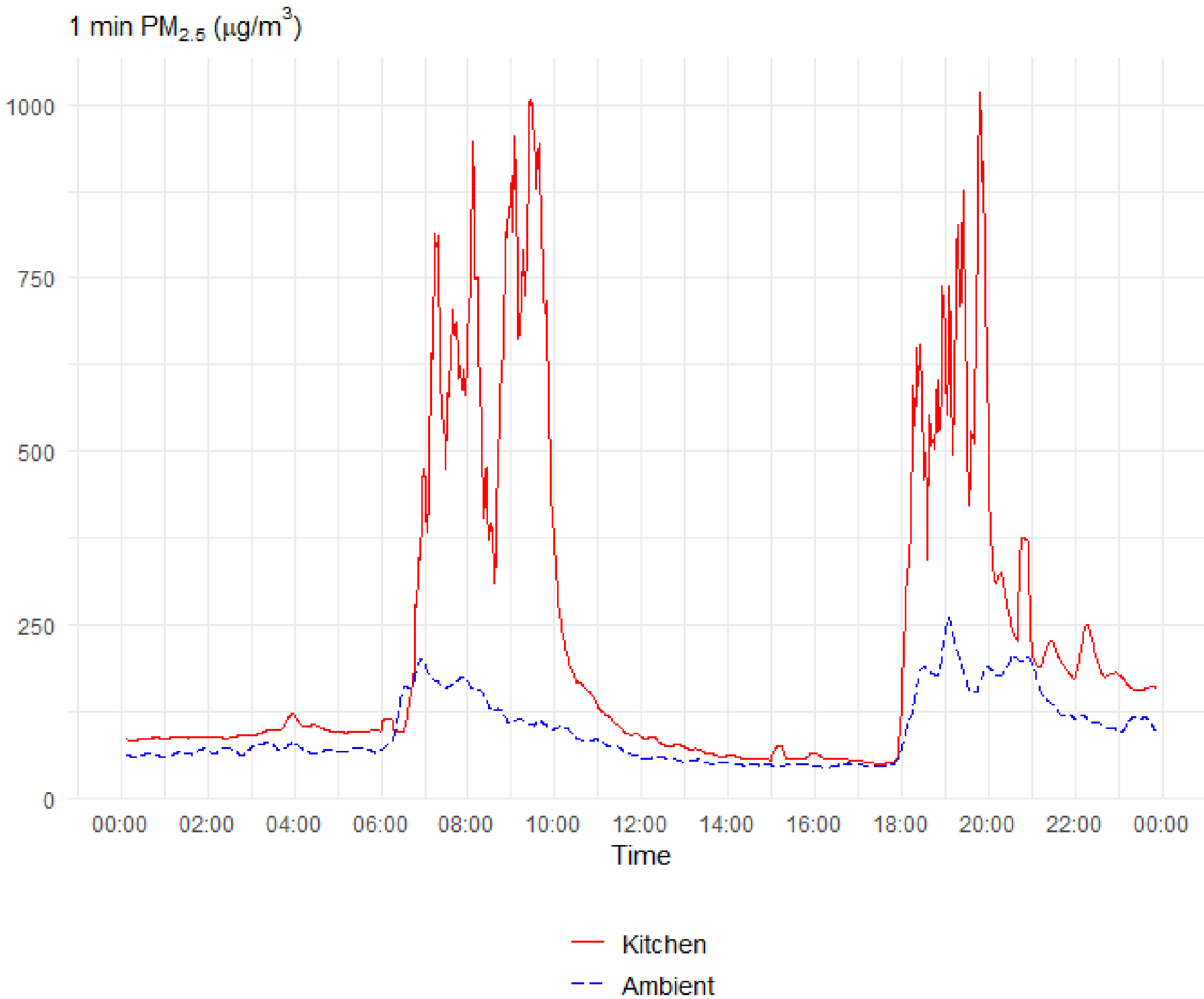

Figure S13: 15-minute moving averages of PM2.5 concentrations over a day in a household

Notes: The solid line plots 15-minute moving averages of PM2.5 ($\mu g/m^3$) concentrations over a day (10 February 2019) measured in the kitchen of a household that cooks with solid fuels. The dashed line shows data from an outdoor sensor in the same village on the same date.

S4 Average PM2.5 in different household kitchen categories

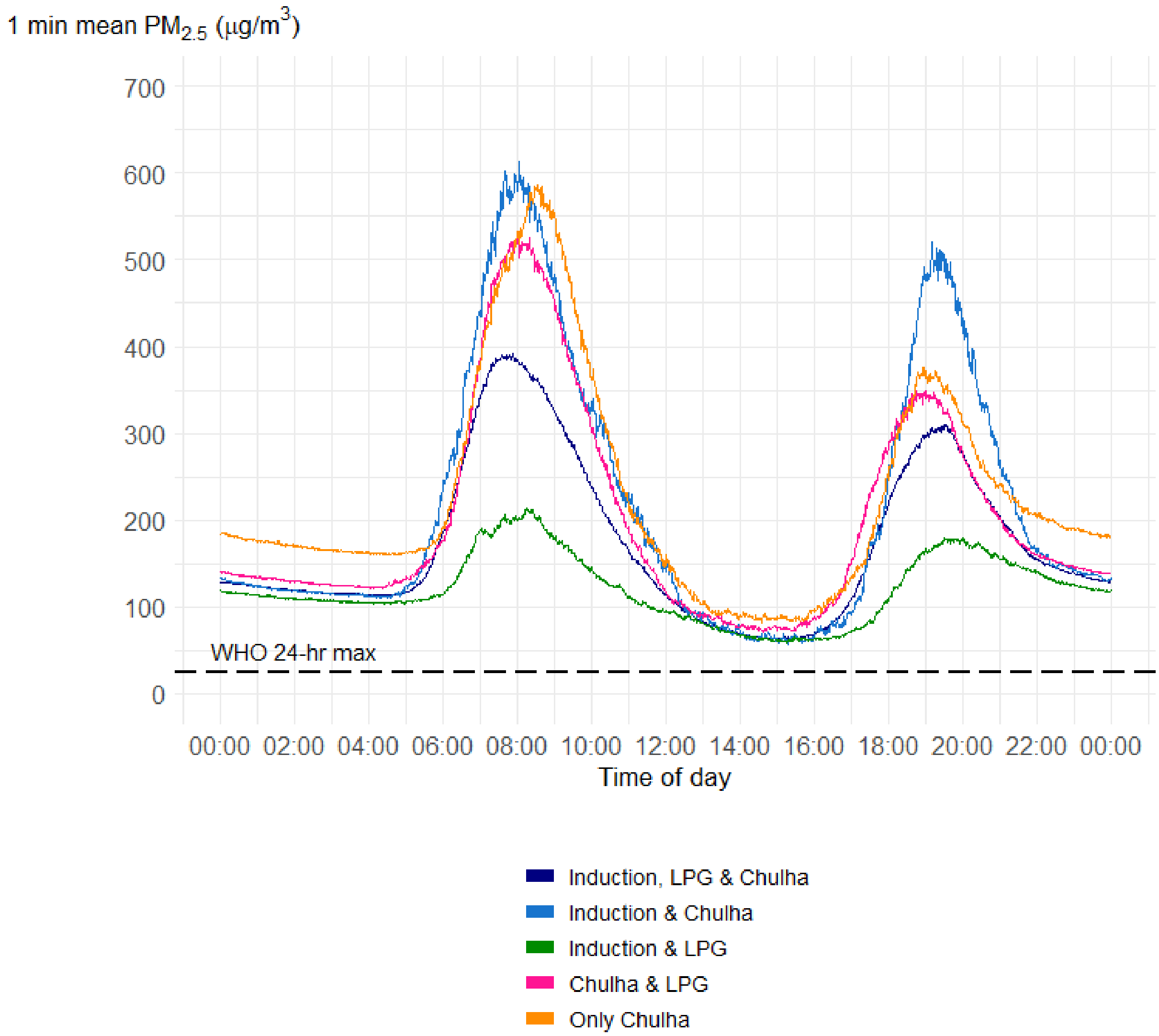

Figure S14: Mean PM2.5 $\mu g/m^3$ in the sample villages and various household kitchen categories during each minute of the day.

Notes: PM2.5 $\mu g/m^3$ for each minute of the day has been averaged over the twelve-month period 1 September 2018 to 19 September 2019. Ambient PM2.5 is averaged over the outdoor sensors in each of the 8 villages. Table 1 shows the number of households in each of the five categories depicted in this figure.

S5 Electricity availability and outages

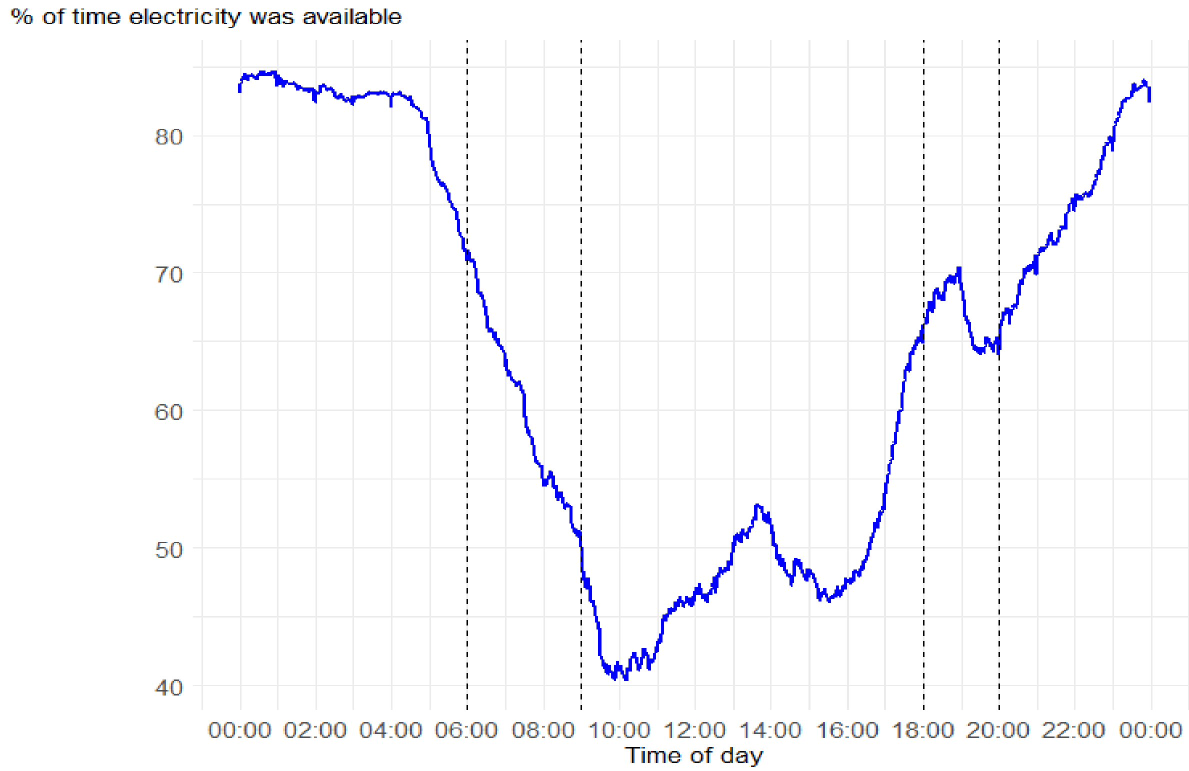

Figure S15: Percentage of days electricity was available for each minute of the day

Notes: This is an average from voltmeters on the ten lines from which the sample households drew their power from 1 September 2018 to 19 September 2019. The vertical dotted lines are the medians of start and end of morning and evening cooking times as reported from the household surveys.

S6 Mean induction use share

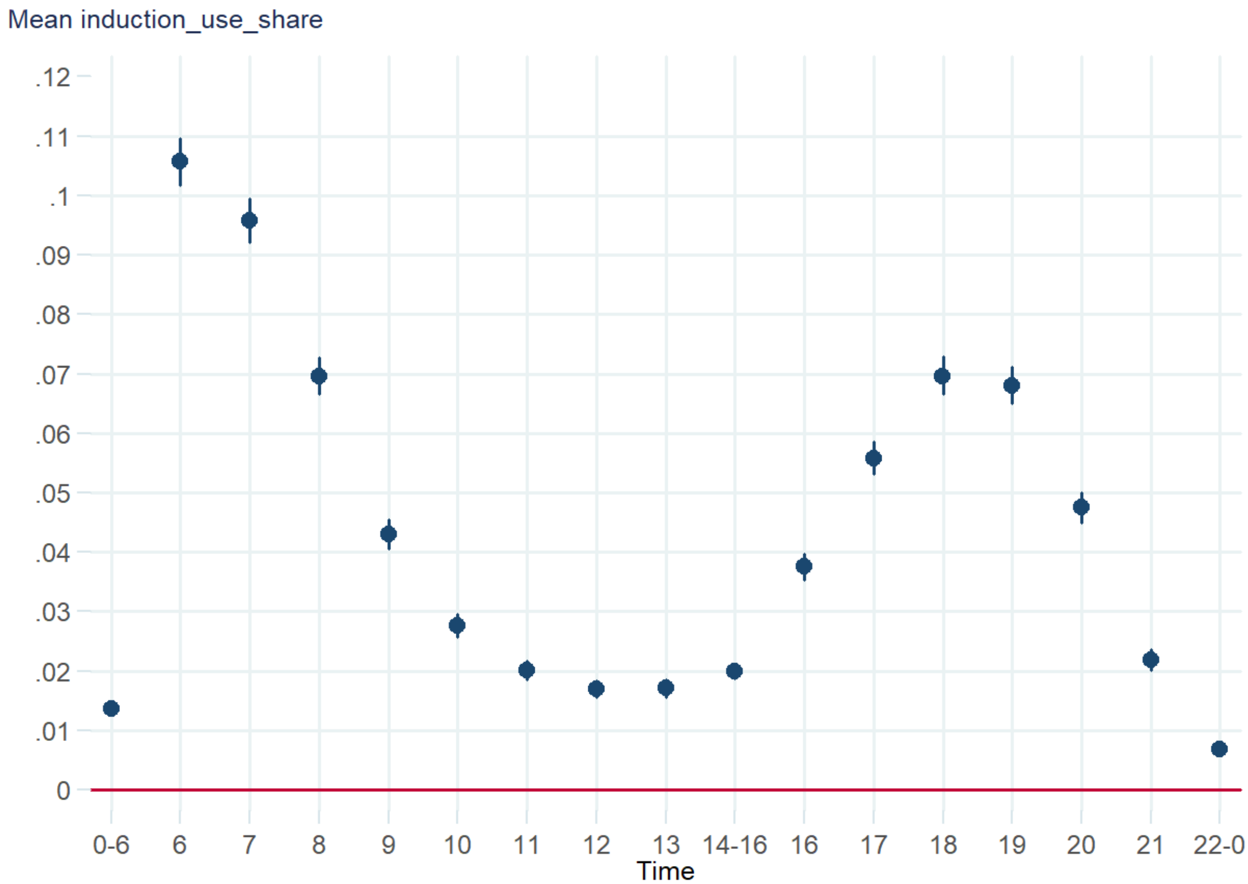

Figure S16: Period-wise shares of time in which induction stove has been used by households, averaged over all induction-stove owning households from 1 September 2018 to 19 September 2019.

Notes: The time labels on the x axis refer to periods beginning with that particular time (eg. 0-6 refers to 12 AM - 5:59 AM and 6 refers to 6 AM - 6:59 AM). Averages have been calculated using induction use data for all induction-owning households. Figure shows 95% confidence intervals of mean values.

S7 Robustness checks

S7.1 LASSO estimation

Since we have 24 variables of interest in our regression models - the electricity shares during each hour of the day, it is possible that some of the coefficients will appear to be statistically significant by chance. We use the LASSO estimator to check whether any of the 24 electricity shares are poor predictors of the left-hand-side variables in our regression models.
We use the program rlasso available in the STATA package 'LASSOPACK' for estimation (Ahrens, Hansen, and Schaffer 2020). The LASSO estimator $\hat{\beta}$ solves the following problem.

$$\min_{\beta} \frac{1}{N} RSS + \frac{\lambda}{N} * ||\psi * \beta||_1 \tag{S2}$$

where $RSS = \sum_{i=1}^{N} (y_i - x_i' \beta)^2$ denotes the residual sum of squares,
β is a p-dimensional parameter vector,
λ is the overall penalty level,
$||.||_1$ denotes the L1-norm, i.e. $\sum_i |a_i|$,
ψ is a p by p diagonal matrix of predictor-specific penalty loadings (rLASSO treats ψ as a row vector),
N is the number of observations

We partial-out month-hour and household-hour variables prior to construction of penalty loadings since we want to use only between-day variation in electricity shares in each period to estimate effects on PM2.5. Heteroskedastic and autocorrelation-consistent (HAC) penalty loadings (Chernozhukov et al. 2021) have been obtained using the bw() option with the robust option. The default Bartlett kernel with bandwidth 11 (order $T^{1/4}$) has been used.

S7.1.1 LASSO estimation of Equation 1 : Induction-stove-owning households with *chulha*

The variables selected for inclusion by the LASSO estimator are shown in the first column of Table S7. The second column shows the LASSO estimates and the third column lists the Ordinary Least Squares (OLS) coefficient estimates from the model estimated after dropping the non-selected coefficients.

Table S7: LASSO Estimation of Equation 1 with dependent variable kitchen PM2.5 on the primary subsample of induction-stove-owning households with *chulhas*

Selected	LASSO	Post-est OLS
Ambient_Pollution	0.2822	0.3006
elec_6	-2.9119	-25.8859
elec_7	-29.2644	-54.5689
elec_8	-16.5691	-40.9609
elec_16	-1.7719	-15.7593
elec_17	-1.7139	-22.7862
elec_18	-19.2343	-45.4534
elec_19	-6.4340	-31.8523
Obs	228184	
R-Sq	0.046	

Notes: "elec_i" denotes the share of hour i during which electricity was available. Month-hour, household-hour, and day-of-the-week fixed effects partialled-out prior to LASSO estimation. Only ambient PM2.5 and electricity shares in each of the 24 hours were included in the set of variables to be penalized.

S7.2 Equation 1 with hour - lag of electricity share as an additional control variable

As a robustness check, we re-estimated Equation 1 after including electricity shares lagged by one hour as shown in Equation S3 below.

$$
\begin{aligned}
Kitchen\_PM2.5_{hljt} = a_{hj} + d_{mj} + \gamma Ambient\_PM2.5_{ljt} + \sum_{j=1}^{24} \mu_j Elec\_share_{ljt} * hour_j \\
+ \sum_{j=2}^{24} \eta_j Elec\_share_{lj-1t} * hour_j + \epsilon_{hljt}
\end{aligned}
\tag{S3}
$$

where $Kitchen\_PM2.5_{hljt}$ is the average PM2.5 concentration in household h on electricity line l on day t in hour j, a_{hj} is a household-period fixed effect, d_{mj} is a month-period fixed effect, $Ambient\_PM2.5_{ljt}$ is the average ambient PM2.5 concentration in the area with electricity line l on day t in period j, $Elec\_share_{ljt}$ is the share of time in hour j on day t for which electricity was supplied in line l, $hour_j$ is a dummy variable for hour j, ϵ_{hljt} is the residual error term for household h on day t in hour j on line l.

As seen in Figure S17, the coefficients on electricity shares show a pattern similar to the one depicted in Figure 3, although they are less precisely estimated. Figure S18 shows that electricity availability in the previous hour reduces pollution to a much lesser extent when compared with its contemporaneous effect. The effect of the one-period lag may be due to a decision to start cooking with an induction stove earlier, rather than with a *chulha*, when electricity is available, a shift that could carry over into the subsequent period.

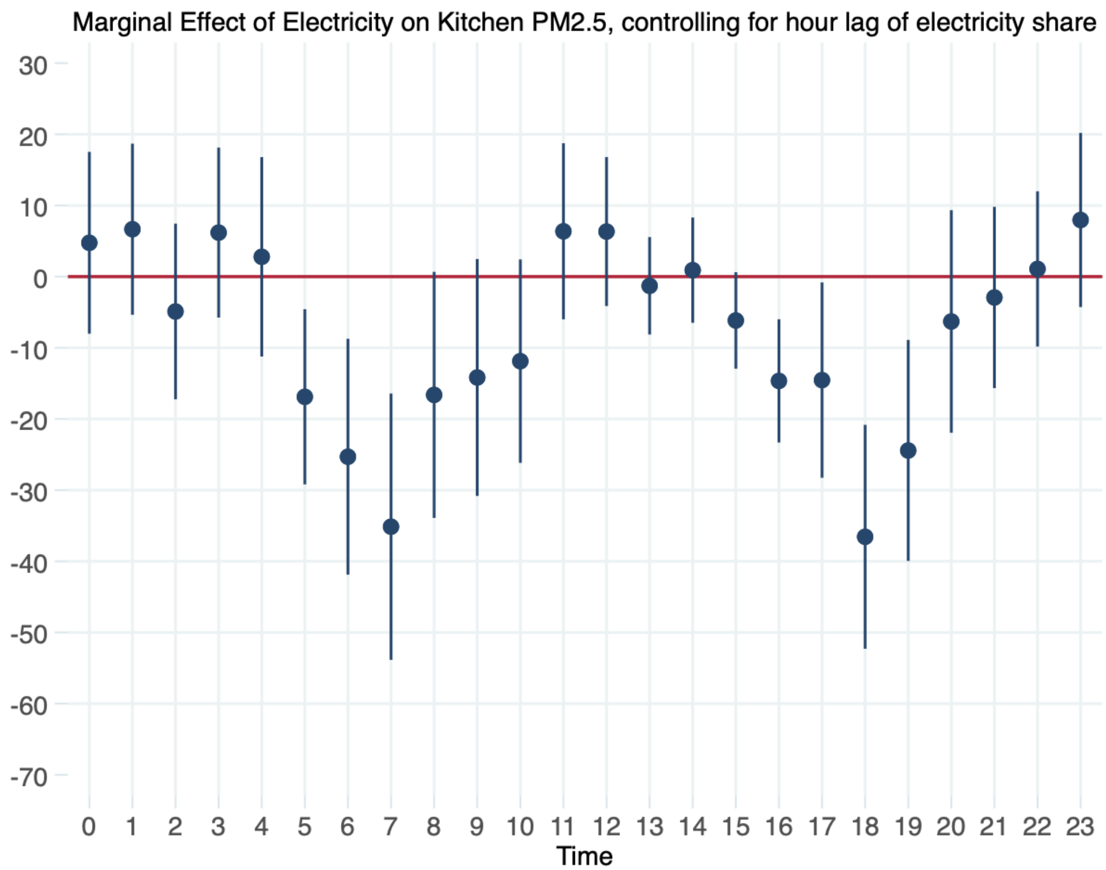

Figure S17: Hour-wise marginal effects of electricity supply on kitchen PM2.5 for induction-owning households with *chulha*, controlling for electricity shares lagged by one hour

Notes: The time labels on the x axis refer to hours beginning with that particular time (eg. 6 refers to 6 AM - 6:59 AM). Plots depict coefficient μ_j from Equation S3. 95% confidence intervals computed using Driscoll-Kraay standard errors that allow for cross-sectional and temporal dependence.

Electricity lagged by one hour coefficients from Equation S3

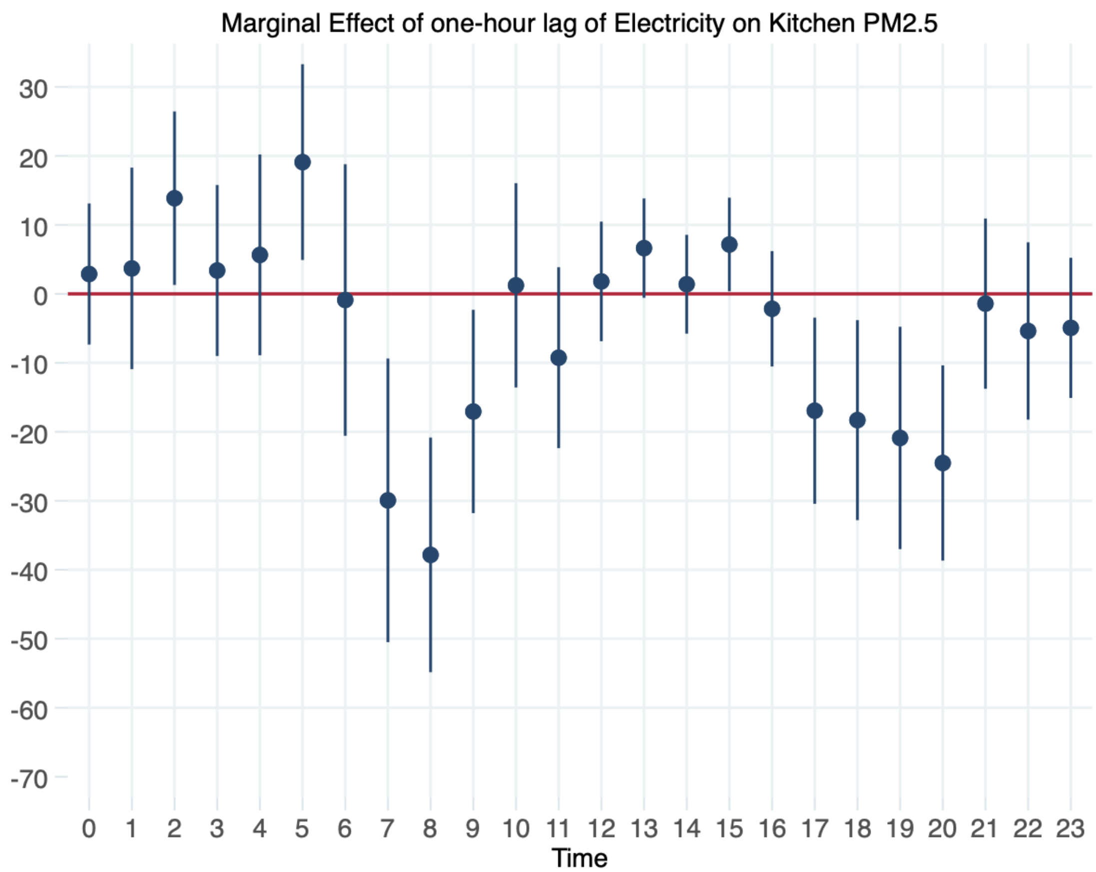

Figure S18: Hour-wise marginal effects of previous hour's electricity supply on kitchen PM2.5 for induction-owning households with *chulha*

Notes: The time labels on the x axis refer to periods beginning with that particular time (eg. 6 refers to 6 AM - 6:59 AM). The plots depict coefficient η_j from Equation S3. 95% confidence intervals computed using Driscoll-Kraay standard errors that allow for cross-sectional and temporal dependence.

S7.3 Equation 1 with day - lag of electricity share as an additional control variable

We ran a specification similar to Equation 1 after including electricity shares lagged by one day as shown in Equation S4 below.

$$
\begin{aligned}
Kitchen\_PM2.5_{hljt} = a_{hj} + d_{mj} + \gamma Ambient\_PM2.5_{ljt} + \sum_{j=1}^{24} \alpha_j Elec\_share_{ljt} * Period_j \\
+ \sum_{j=1}^{24} \theta_j Elec\_share_{ljt-1} * hour_j + \epsilon_{hljt}
\end{aligned}
\tag{S4}
$$

where $Kitchen\_PM2.5_{hljt}$ is the average PM2.5 concentration in household h on electricity line l on day t in hour j, a_{hj} is a household-hour fixed effect, d_{mj} is a month-hour fixed effect, $Ambient\_PM2.5_{ljt}$ is the average ambient PM2.5 concentration in the area with electricity line l on day t in hour j, $Elec\_share_{ljt}$ is the share of time in hour j on day t for which electricity was supplied in line l, $hour_j$ is a dummy variable for hour j, ϵ_{hljt} is the residual error term for household h on day t in hour j on line l

The pattern shown by coefficients on electricity shares in Figure S19 is similar to the one seen in Figure 3. However, Figure S20 shows no such pattern of effects of the previous day's electricity shares. This confirms that adjustments such as the decision to start cooking with an induction stove earlier, rather than with a *chulha*, when electricity is available, only occur within the same day.

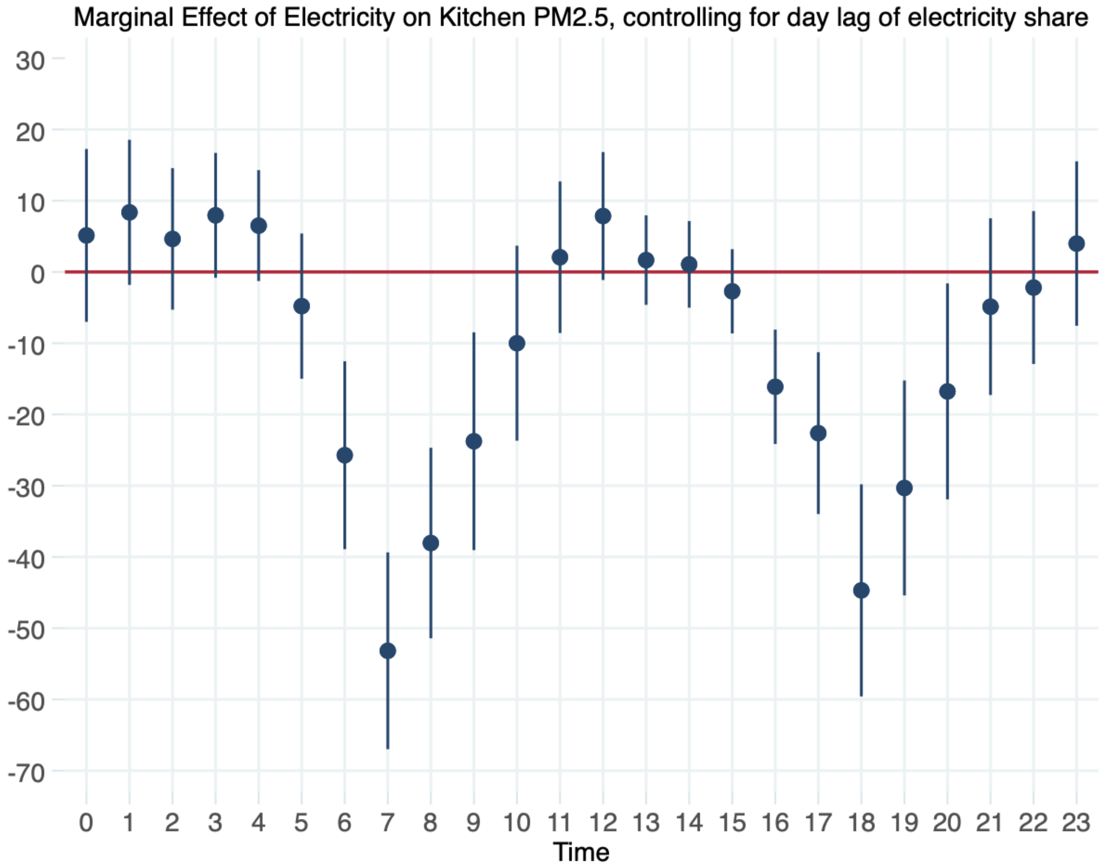

Figure S19: Hour-wise marginal effects of electricity supply on kitchen PM2.5 for induction-owning households with *chulha*, controlling for electricity shares lagged by day.

Notes: The time labels on the x axis refer to periods beginning with that particular time (eg. 6 refers to 6 AM - 6:59 AM). The plots depict coefficient α_j from Equation S4. 95% confidence intervals computed using Driscoll-Kraay standard errors that allow for cross-sectional and temporal dependence.

Day-lag electricity coefficients from Equation S4

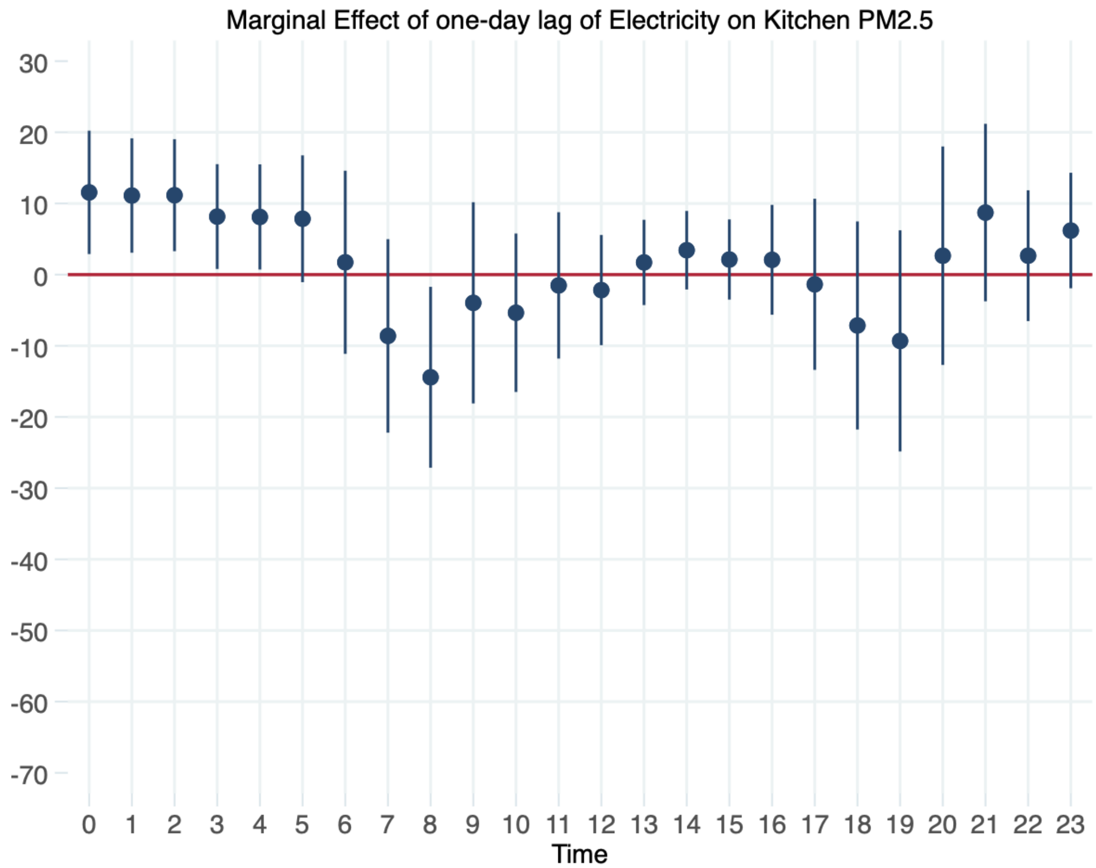

Figure S20: Hour-wise marginal effects of previous day's electricity supply on kitchen PM2.5 for induction-owning households with *chulha*.

Notes: The time labels on the x axis refer to periods beginning with that particular time (eg. 6 refers to 6 AM - 6:59 AM). The plots depict coefficient θ_j from Equation S4. 95% confidence intervals computed using Driscoll-Kraay standard errors that allow for cross-sectional and temporal dependence.

S7.4 Equation 1 for the placebo subsample without induction stoves

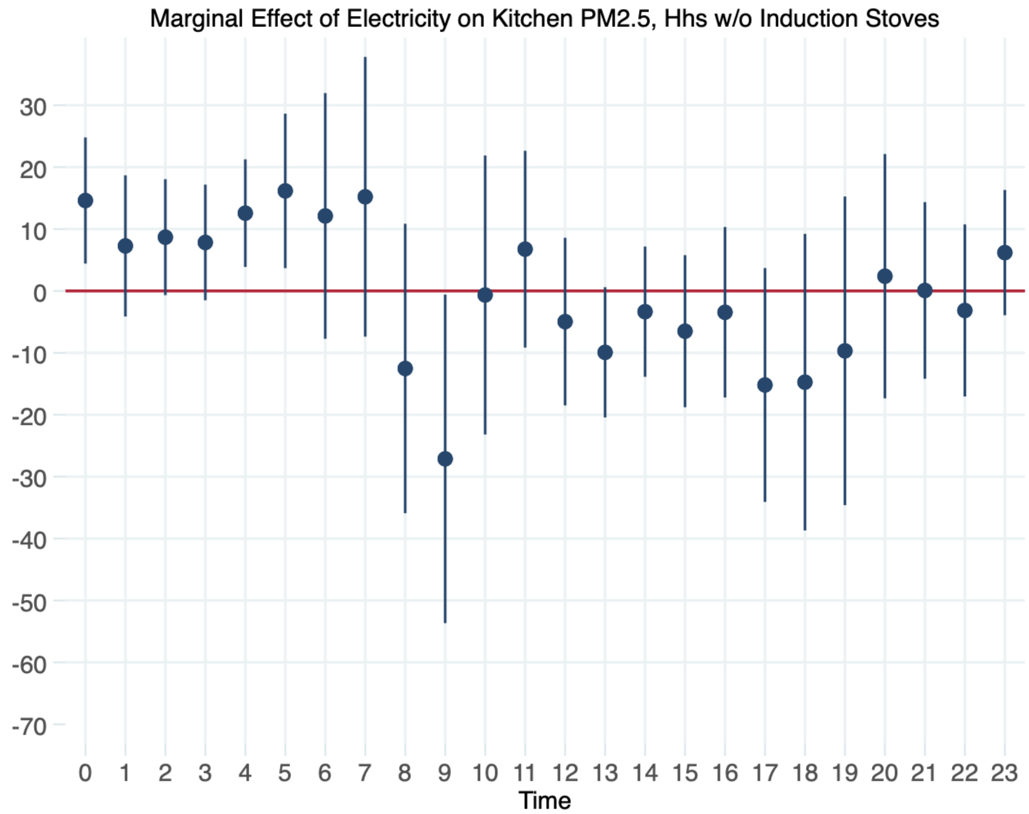

Figure S21: Period-wise marginal effects of electricity supply on kitchen PM2.5 for the 15 households with a *chulha* (solid-fuel stove) but without induction stoves

Notes: The plots depict coefficient μ_j from Equation 1. 95% confidence intervals have been computed using Driscoll-Kraay standard errors that allow for cross-sectional and temporal dependence.

S7.5 Equation 1 for the placebo subsample with only clean stoves

Equation 1 was run on the subsample of households with only clean stoves as a placebo. As shown in Figure S22, the reductions in PM2.5 due to electricity availability are not only much smaller, but also insignificant in most periods in this subsample. Induction stove use in the clean-stove subsample responds in the same way to electricity availability as in the primary subsample (Figures S26, **??**), suggesting that it substitutes for LPG.

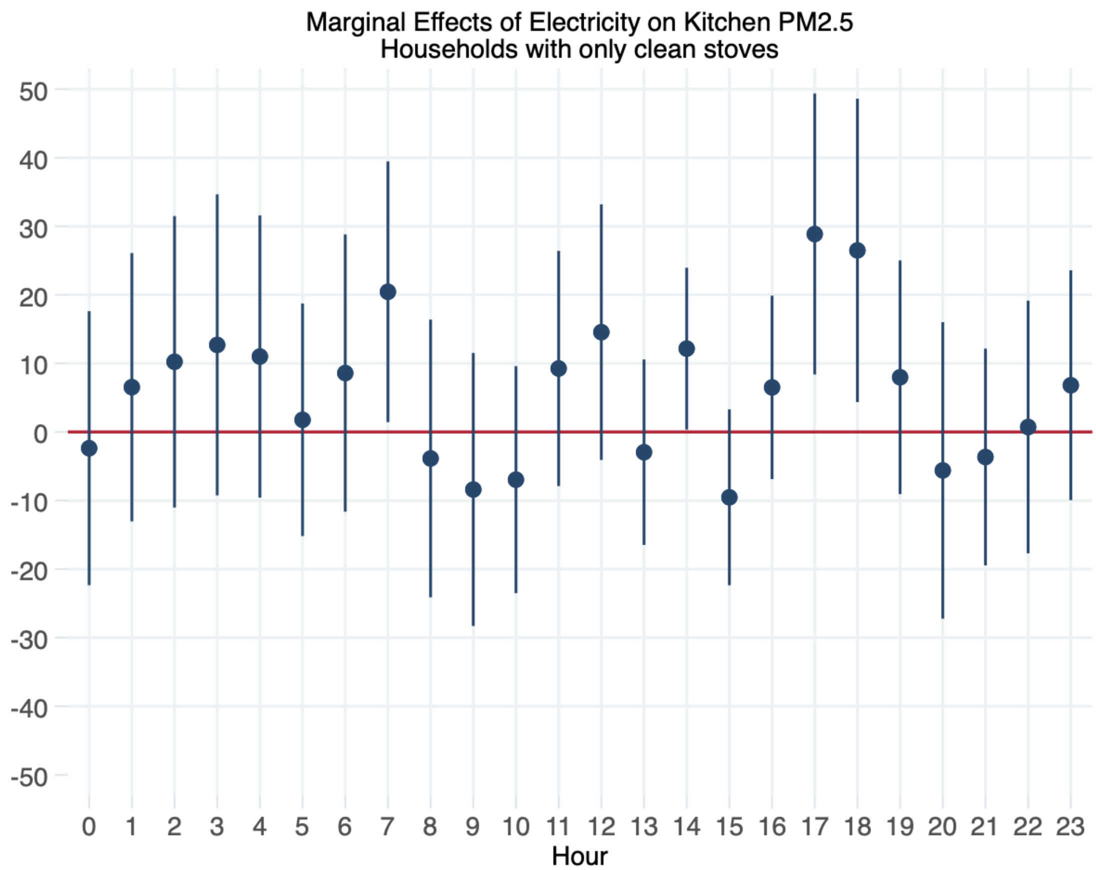

Figure S22: Hour-wise marginal effects of electricity supply on kitchen PM2.5 for the 6 households with only clean stoves (induction and LPG, but no *chulha*)

Notes: The time labels refer to hours beginning with that particular time (e.g. 6 refers to 6 AM - 6:59 AM). The plots depict coefficient μ_j from Equation 1. 95% confidence intervals have been computed using Driscoll-Kraay standard errors robust to cross-sectional and temporal dependence.

S7.6 LASSO estimation of Equation 1 : Placebo subsample with only clean stoves

We re-estimated Equation 1 using the LASSO estimator for the placebo subsample of 6 households with only clean stoves. In line with our expectations, Table S8 shows that none of the electricity shares were selected for inclusion in the model indicating they were poor predictors of PM2.5.

Table S8: LASSO Estimation of Equation 1 (Subsample of 6 households with only clean stoves)

Selected	LASSO	Post-est OLS
Ambient_PM2.5	0.2626	0.3032
Obs	30933	
R-Sq	0.071	

Notes: Month-hour and household-hour variables partialled-out prior to LASSO estimation. Only ambient PM2.5 and electricity share interacted with period variables were included in the set of variables to be penalized.

S7.7 LASSO estimation of Equation 1 : Placebo subsample of households without induction stoves

We re-estimated Equation 1 using the LASSO estimator for the placebo subsample of households without induction stoves. As seen in Table S9, all electricity shares were dropped from the model indicating that they had little predictive power.

Table S9: LASSO Estimation of Equation 1 with dependent variable kitchen PM2.5 on the placebo subsample of households without induction stoves

Selected	LASSO	Post-est OLS
Ambient_PM2.5	0.5014	0.5452
Obs	56108	
R-Sq	0.126	

Notes: Month-hour and household-hour variables partialled-out prior to LASSO estimation. Only ambient PM2.5 and electricity share interacted with period variables were included in the set of variables to be penalized.

S7.8 Equation 1 for households that use and don't use a fan in the kitchen

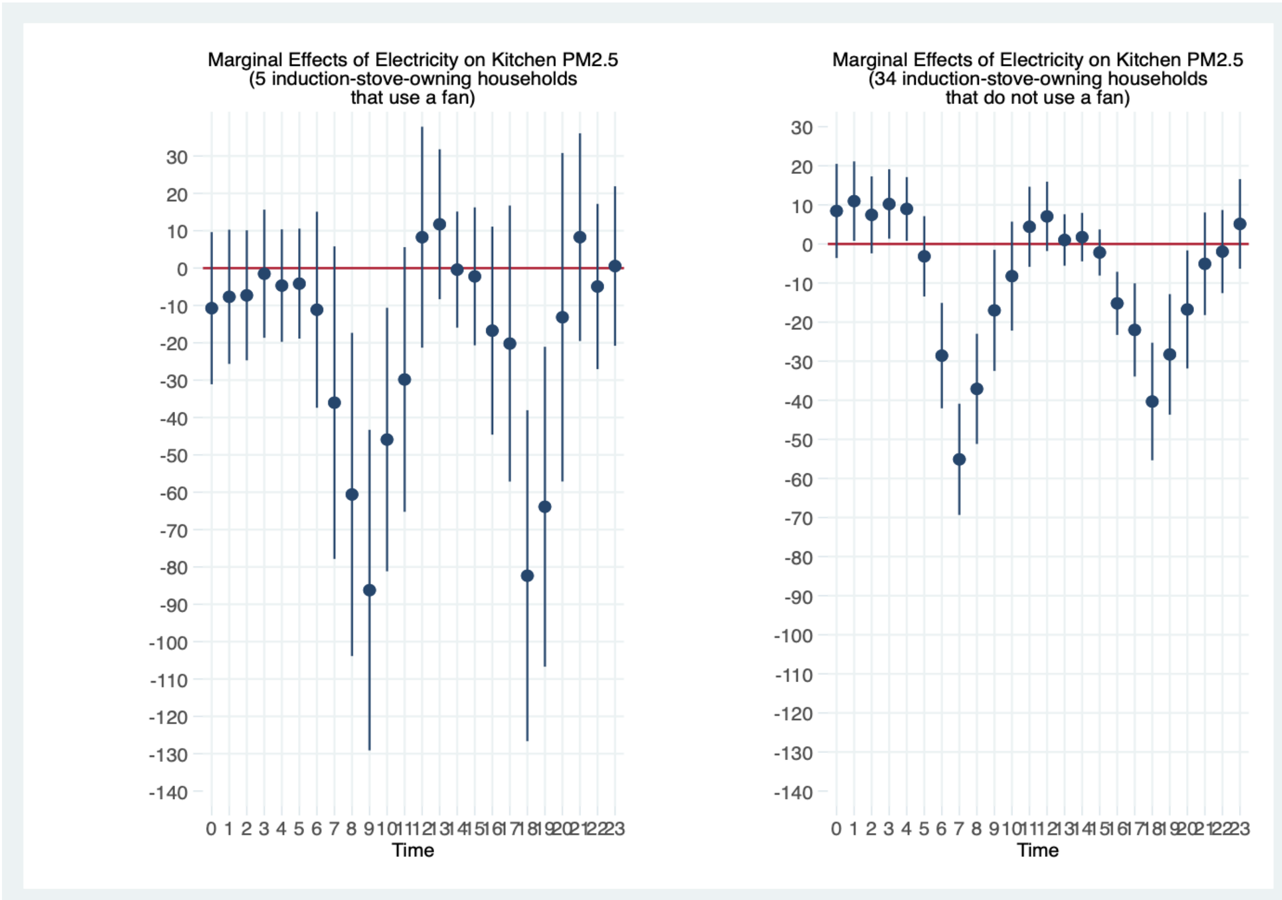

Figure S23: Hour-wise marginal effects of electricity supply on kitchen PM2.5 for induction-stove-owning households with a *chulha* (solid-fuel stove) by use of fans in the kitchen

Notes: Plots depict the coefficients μ_j from Equation 1. Left panel: Households that use fans in the kitchen during or after cooking. Right panel: Households that do not do so. 95% confidence intervals computed using Driscoll-Kraay standard errors that are robust to cross-sectional and temporal dependence.

S7.9 Equation 1 for households that have and do not have power backup

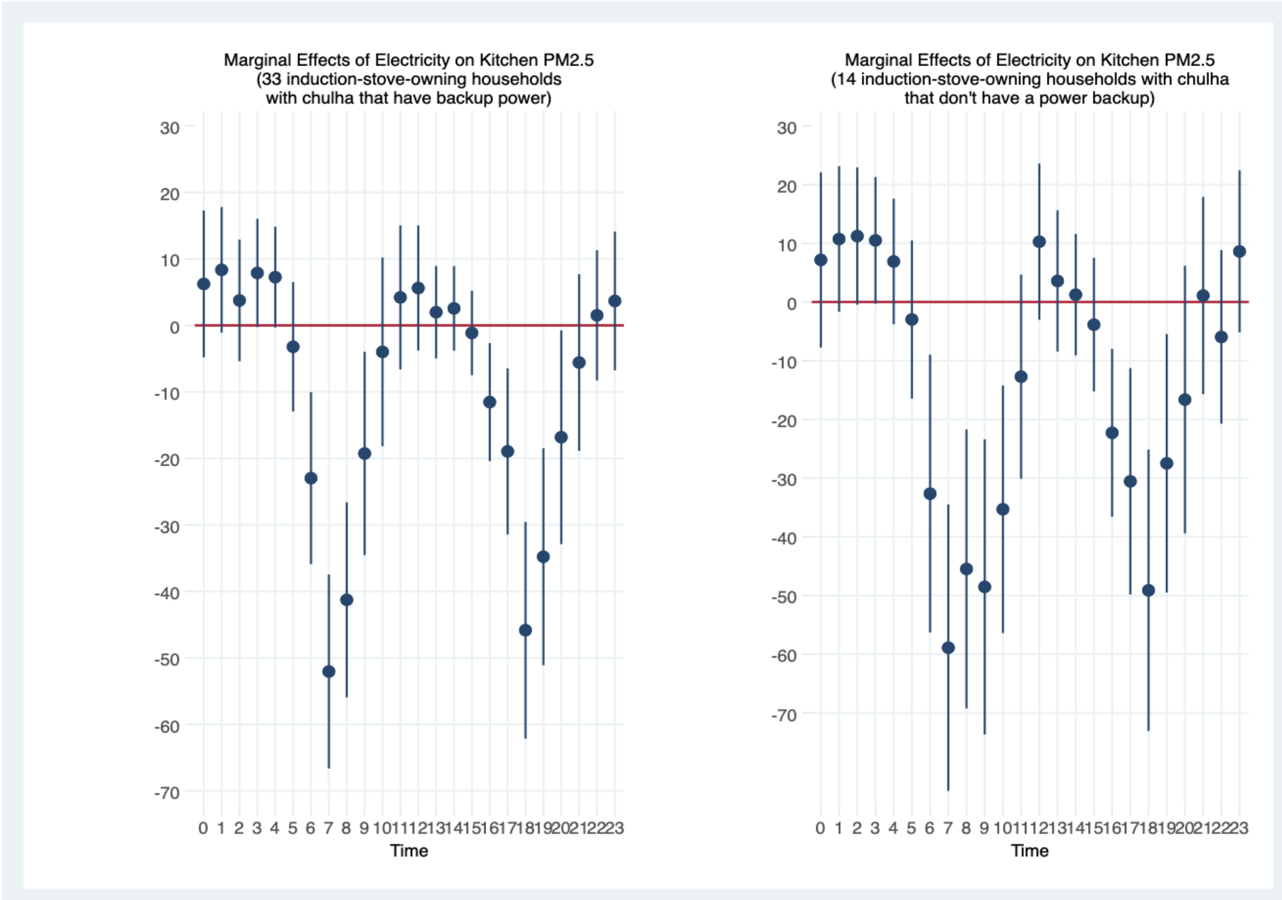

Figure S24: Hour-wise marginal effects of electricity supply on kitchen PM2.5 for induction-stove-owning households with a *chulha* (solid-fuel stove) by availability of backup power for lighting

Notes: Plots depict the coefficients μ_j from Equation 1. Left panel: Households with backup power. Right panel: Households without backup power. 95% confidence intervals computed using Driscoll-Kraay standard errors that are robust to cross-sectional and temporal dependence.

S7.10 Modified Equation 1 with low and normal-voltage electricity shares as control variables

We ran a modified version of Equation 1 in which the share of the period electricity is available is replaced by two variables, the share of the period low-voltage (100-200V) electricity is available, and the share of the period that near-normal-voltage (>200V) electricity is available as shown in Equation S5 below.

$$Kitchen\_PM2.5_{hljt} = a_{hj} + d_{sj} + \gamma Ambient\_PM2.5_{ljt} + \sum_{j=1}^{17} \alpha_j Low\_volt\_Elec\_share_{ljt} * Period_j + \sum_{j=1}^{17} \theta_j Normal\_volt\_Elec\_share_{ljt} * Period_j + \epsilon_{hljt} \quad \text{(S5)}$$

where $Kitchen\_PM2.5_{hljt}$ is the average PM2.5 concentration in household h on electricity line l on day t in period j, a_{hj} is a household-period fixed effect, d_{sj} is a season-period fixed effect, $Ambient\_PM2.5_{ljt}$ is the average ambient PM2.5 concentration in the area with electricity line l on day t in period j, $Low\_volt\_Elec\_share_{ljt}$ is the share of time in period j on day t for which low-voltage electricity was supplied in line l, $Normal\_volt\_Elec\_share_{ljt}$ is the share of time in period j on day t for which normal-voltage electricity was supplied in line l, $Period_j$ is a dummy variable for period j, ϵ_{hljt} is the residual error term for household h on day t in period j on line l

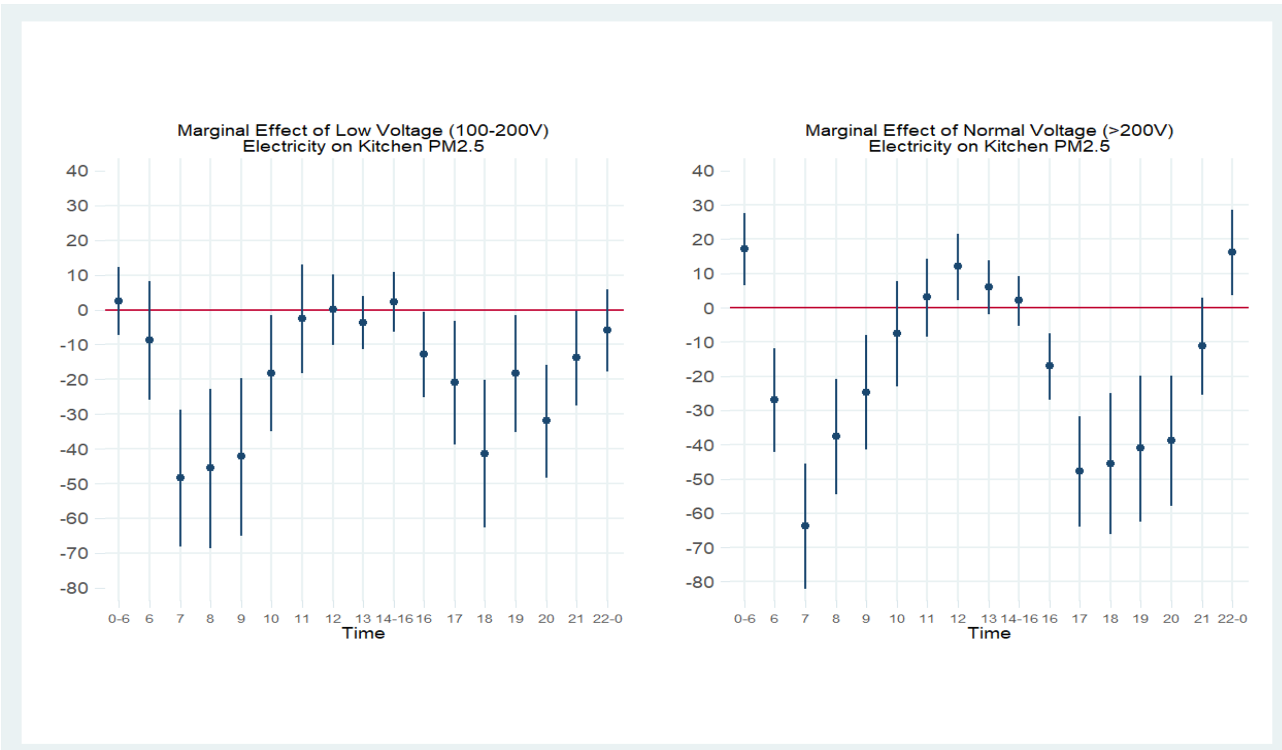

Figure S25: Period-wise marginal effects of low and normal voltage electricity on kitchen PM2.5 for induction-stove-owning households with *chulha*

Notes: The time labels on the x axis refer to periods beginning with that particular time (eg. 0-6 refers to midnight - 5:59 AM and 6 refers to 6 AM - 6:59 AM). The plots in the left panel depict coefficient α_j from Equation S5. The plots in the right panel depict coefficient θ_j from Equation S5. 95% confidence intervals computed using Driscoll-Kraay standard errors that allow for cross-sectional and temporal dependence.

S8 IV Regressions - Detailed Results

S8.1 Estimates for Equation 2 (Second Stage of IV Regression)

Table S10: Equation (2)

	0	1	2	3	4
induction_use_share	-3339.5309	2970.6680	561.6868	-12284.5549	844.6813
	(6634.9625)	(3252.6433)	(4851.4548)	(38563.5903)	(653.7015)
	[NA]	[NA]	[NA]	[NA]	[1049.892]
Ambient_Pollution	0.3880***	0.4127***	0.3715***	0.3255**	0.3247***
	(0.0700)	(0.0680)	(0.0730)	(0.1393)	(0.0746)
Obs	3189	3163	3153	3141	3149
R-Sq	-0.362	0.026	0.573	-6.213	0.293
Kleibergen-Paap rk Wald F statistic	0.325	2.535	2.664	0.118	11.883

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parenthesis, Lee et al. 2021 adjusted standard errors for in brackets

Table S11: Equation (2) contd.

	5	6	7	8	9
induction_use_share	-41.7150	-225.5968***	-444.9707***	-407.7511***	-82.5507
	(102.1713)	(87.0233)	(90.6950)	(91.1825)	(159.8459)
	[104.216]	[87.023]	[90.6950]	[91.1825]	[159.845]
Ambient_Pollution	0.3870***	0.2562***	0.3051***	0.2657***	0.2464***
	(0.0735)	(0.0537)	(0.0635)	(0.0614)	(0.0518)
Obs	3166	3188	3187	3216	3218
R-Sq	0.316	0.431	0.376	0.377	0.375
Kleibergen-Paap rk Wald F statistic	87.206	106.105	172.024	130.978	108.169

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Standard errors in parenthesis, Lee et al. 2021 adjusted standard errors in brackets

Table S12: Equation (2) contd.

	10	11	12	13	14
induction_use_share	103.6628	108.8162	153.5697	4.7101	149.7756
	(217.2444)	(257.4419)	(287.9337)	(268.2994)	(264.2224)
	[228.687]	[302.718]	[344.587]	[297.667]	[1101.578]
Ambient_Pollution	0.2380***	0.1844***	0.1771***	0.0928**	0.0887***
	(0.0597)	(0.0558)	(0.0572)	(0.0407)	(0.0287)
Obs	3196	3202	3245	3263	3266
R-Sq	0.332	0.316	0.249	0.144	0.124
Kleibergen-Paap rk Wald F statistic	80.302	33.086	30.386	45.960	48.585

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Standard errors in parenthesis, Lee et al. 2021 adjusted standard errors for in brackets

Table S13: Equation (2) contd.

	15	16	17	18	19
induction_use_share	43.4343	-101.2363	-150.7371	-293.7736***	-450.9189**
	(121.0090)	(98.9530)	(98.4872)	(112.1421)	(185.0617)
	[126.586]	[100.387]	[98.487]	[114.146]	[192.762]
Ambient_Pollution	] 0.0882***	0.0816**	0.2057***	0.2189***	0.2328***
	(0.0285)	(0.0326)	(0.0518)	(0.0469)	(0.0486)
Obs	3276	3308	3344	3341	3310
R-Sq	0.116	0.121	0.351	0.469	0.292
Kleibergen-Paap rk Wald F statistic	70.116	91.889	106.286	89.066	72.894

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Standard errors in parenthesis, Lee et al. 2021 adjusted standard errors for in brackets

Table S14: Equation (2) contd.

	20	21	22	23
induction_use_share	-297.3164	-790.2788	-436.6537	-132.7932
	(333.4545)	(661.7319)	(1001.9221)	(1728.3976)
	[381.275]	[762.831]	[1561.456]	[NA]
Ambient_Pollution	0.3617***	0.4033***	0.4364***	0.4054***
	(0.0650)	(0.0688)	(0.0789)	(0.0655)
Obs	3286	3259	3232	3221
R-Sq	0.340	0.407	0.576	0.604
Kleibergen-Paap rk Wald F statistic	38.421	36.756	12.731	0.848

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Standard errors in parenthesis, Lee et al. 2021 adjusted standard errors for induction$_{u}se_{s}harein$

S8.2 Estimates for Equation 3 (First Stage of IV Regression)

Table S15: Equation (3)

	0	1	2	3	4
electricity_supply_share	-0.0017	0.0027	0.0015	-0.0006	0.0096***
	(0.0029)	(0.0017)	(0.0009)	(0.0018)	(0.0028)
Obs	3189	3163	3153	3141	3149
F statistic	0.325	2.535	2.664	0.118	11.883

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S16: Equation (3) contd.

	5	6	7	8	9
electricity_supply_share	0.0700***	0.1277***	0.1444***	0.1219***	0.0765***
	(0.0075)	(0.0124)	(0.0110)	(0.0106)	(0.0074)
Obs	3166	3188	3187	3216	3218
F statistic	87.206	106.105	172.024	130.978	108.169

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S17: Equation (3) contd.

	10	11	12	13	14
electricity_supply_share	0.0499***	0.0316***	0.0304***	0.0233***	0.0237***
	(0.0056)	(0.0055)	(0.0055)	(0.0034)	(0.0034)
Obs	3196	3202	3245	3263	3266
F statistic	80.302	33.086	30.386	45.960	48.585

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S18: Equation (3) contd.

	15	16	17	18
electricity_supply_share	0.0431***	0.0658***	0.1068***	0.1088***
	(0.0051)	(0.0069)	(0.0104)	(0.0115)
Obs	3276	3308	3344	3341
F statistic	70.116	91.889	106.286	89.066

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S19: Equation (3) contd.

	19	20	21	22	23
electricity_supply_share	0.0771***	0.0426***	0.0153***	0.0059***	-0.0037
	(0.0090)	(0.0069)	(0.0025)	(0.0016)	(0.0040)
Obs	3310	3286	3259	3232	3221
F statistic	72.894	38.421	36.756	12.731	0.848

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

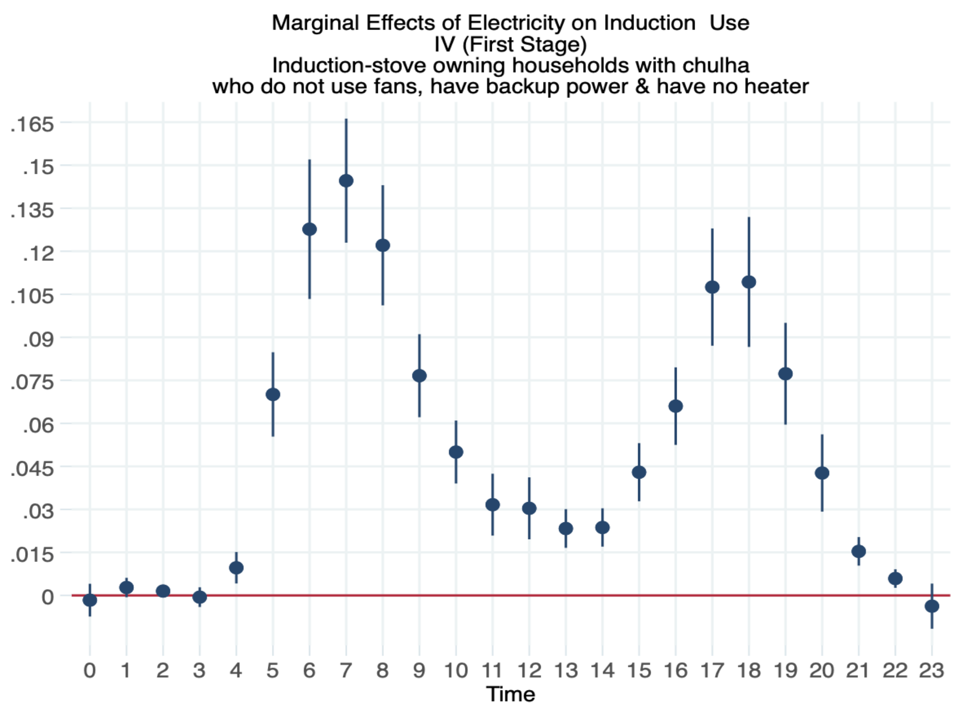

Figure S26: Marginal effects of electricity availability on induction stove use for induction-stove-owning households with a *chulha* (solid-fuel stove)

Notes: The sample includes 22 households that satisfied the exclusion restriction. Plots depict the coefficients ν_j from the first-stage Equation 3. 95% confidence intervals computed using Driscoll-Kraay standard errors robust to cross-sectional and temporal dependence.