Transient air pollution peaks and the adoption of improved cookstoves among the urban poor

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Abstract

Persistent exposure to air pollution can substantially shorten life expectancy, but how exposure affects health is subject to ongoing policy and regulatory debate. More than a billion urban poor are exposed to both transient peaks in air pollution caused by indoor biomass cooking as well as high levels of ambient air pollution caused for example by external industrial and transportation sources. Can the reductions in transient air pollution peaks resulting from improved cookstove adoption generate health benefits in these contexts? We leverage experimental variation to study this question. For more than 3 years after adoption, improved stoves reduce peak PM2.5 exposure during cooking by $52 \mu g/m^3$ (42%). However, average ambient pollution of $38 \mu g/m^3$ largely negates impacts on daily average exposure. These impacts reduce self-reported short-term respiratory symptoms by 0.24 standard deviations. However, even after 3 years of daily use we find no meaningfully improvements on several measures of chronic health, including blood pressure, blood oxygen, or medical diagnoses. **JEL:** I15, O12, Q53, Q56

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1 Introduction

According to the World Health Organization (2021), air pollution is "the single biggest environmental threat to human health." The Global Burden of Disease study (Lancet, 2017) estimates that it is responsible for 7–9 million premature deaths annually (10-15% of all deaths). In addition to facing high levels of ambient air pollution, many of the world's urban poor use biomass cookstoves that cause even higher transient peaks on a daily basis. But despite rapid global urbanization and widespread use of biomass cookstoves by urban households, the health impacts from cookstoves have been studied almost exclusively in rural settings. While the WHO and many domestic governments regulate annual and 24-hour average concentrations, standards for shorter peaks are subject to ongoing regulatory debate (EPA, 2023). What are the health benefits of reducing cookstove emissions—one of the most notorious sources of air pollution peaks—in contexts with sustained ambient pollution generated by industry or transportation?[1]

To make progress on this question, we conduct a randomized field study in Nairobi, Kenya. We offer randomized subsidies and access to credit to create random variation in the adoption of an improved cookstove, and follow up with study participants after 3.5 years of daily use. To measure individual pollution exposure, each respondent wears a backpack containing two devices that record particulate matter smaller than 1.0 or $2.5\mu m$ (PM1.0 and PM2.5) and parts-per-million of carbon monoxide (CO ppm) on a minute-by-minute basis for 48 hours, capturing both cooking and non-cooking air pollution. High-frequency monitoring allows us to separately identify impacts on mean and peak pollution exposure. A complementary time use survey records each respondent's indoor or outdoor activity during each of those 48 hours. To measure health, we complement quantitative measurements of blood pressure, pulse oximetry, and anthropometrics with detailed self-reports on health symptoms and diagnoses for adults and children. Finally, we use a socio-economic survey to measure behavioral and financial impacts.

The analyses generate three key findings. First, the improved stove reduces peak cooking emissions by 42%. For the control group, peak emissions while cooking are 125 $\mu g/m^3$ higher than their median daily exposure, but improved stove ownership reduces this by 52 $\mu g/m^3$.[2] Average exposure while cooking is 50 $\mu g/m^3$ among the control group and 33 $\mu g/m^3$ for the treatment group (p-val < 0.01); for comparison, average exposure while not cooking is 36 $\mu g/m^3$ for both groups. These results are stable, and relatively precise in part due to the persistence of the adoption subsidies: 86% of respondents have the same adoption status as 3.5 years ago.

Second, high levels of ambient pollution largely negate the mostly transitory reductions in peak cooking emissions. Study participants report cooking for only two hours per day on average (9% of the time). The large reductions in cooking pollution therefore have negligible impacts on mean exposure, which averages 38 $\mu g/m^3$ among the control group ($\hat{\beta}$: –0.8, 95% CI: [-7.5, 5.9]).

Given the limited changes in daily average concentrations, does the reduction in peak cooking

[1]Pervasive charcoal cooking may also increase ambient pollution, but this does not affect whether households can improve their own health privately through improved cookstove adoption.

[2]>55 $\mu g/m^3$ (150 AQI) is 'unhealthy'; >150 $\mu g/m^3$ (200 AQI) is 'very unhealthy' (EPA, 2018).

emissions affect health? We estimate that adoption causes a statistically significant 0.24 standard deviation reduction in an index of transient self-reported respiratory symptoms such as sore throat, headache, cough, and runny nose. These are likely a direct result of reductions in peak emissions: an analysis of the mechanisms confirms that these respiratory symptoms are correlated with peak levels and not with average concentrations. However, we see no impacts on an array of clinical, quantitative health measurements (including blood pressure and blood oxygen), medical diagnoses (including pneumonia), or health-related expenditures.[3] In other words, against a backdrop of high ambient air pollution, the large reductions in peak cooking emissions appear to have had negligible impacts on long-term indicators of health during the 3.5 years of ownership. Participants may have already been aware of this: at baseline, 37% of respondents believed that adoption of the improved stove would have no impact on their health (another 20% believed it would have a small impact), and these beliefs did not predict WTP—unlike beliefs about financial savings.[4]

Billions of urban poor are exposed to high levels of both ambient and own-cooking related emissions on a daily basis. More than 90% of pollution-related deaths occur in low- and middle-income countries (WHO, 2021). For the 4 billion people lacking access to improved stoves (World Bank, 2020), intermittent use of traditional cookstoves is a key driver of transient pollution peaks. Yet most countries—as well as the WHO—only have standards for annual and 24-hour averages (Nazarenko, Pal, and Ariya, 2021). The regulation of shorter peaks is subject to ongoing policy and regulatory debate, for example in the U.S. Environmental Protection Agency's recent review of the National Ambient Air Quality Standards (EPA, 2023), which notes that much research on the impacts of short-term peaks evaluates a single exposure, rather than repeated daily exposure to high peaks. The lack of impact on measurable or chronic health outcomes that we estimate indicates that private actions alone can generate only modest health benefits over the course of 3.5 years for users that face high ambient pollution. While it is possible that benefits would emerge over a longer term, private air pollution reductions may have limited health benefits in cities with the highest ambient air pollution.[5,6]

Our use of personally wearable PM and CO pollution monitoring devices to collect high-frequency, indoor and outdoor air pollution measurements advances our understanding of how transient peaks in air pollution exposure contribute to aggregate air pollution exposure and affect health. Existing research on ambient air pollution almost exclusively evaluates mean daily

[3]We can rule out a 0.14 SD or greater reduction in health diagnoses, and comparing our cardiovascular impacts with the medical literature we can reject a 12% or greater decrease in major cardiovascular events.

[4]Table 4 of Berkouwer and Dean (2022a) reports health and savings beliefs in different units. Standardizing both outcomes yields the following results: increasing health beliefs by 1 SD decreases WTP by \$0.01 (p=0.988) while increasing savings beliefs by 1 SD increases WTP by \$0.79 (p=0.036).

[5]As examples, annual PM2.5 concentrations average 13 $\mu g/m^3$ in Los Angeles and Rome, 30 $\mu g/m^3$ in Kampala and Accra, but 49 $\mu g/m^3$ in Jakarta, 83 $\mu g/m^3$ in Dhaka, and 99 $\mu g/m^3$ in Delhi (IQAir, 2019).

[6]One may be concerned that this threatens external validity. In contexts with even higher ambient concentrations, the subsequent peaks must be even higher and perhaps reducing those has positive health impacts. While we cannot rule this possibility out with our data, it is worth nothing that similarities in cooking technologies likely mean the size of the peaks relative to the ambient concentration are similar across the contexts. This means the peaks are likely to be an even smaller portion of an individuals total pollution exposure in more polluted settings.

exposure.[7] Gong et al. (2023), He, Fan, and Zhou (2016), and La Nauze and Severnini (2021) study non-linearity in the dose-response function but focus on concavity in daily average pollution exposure. Caplan and Acharya (2019), Cropper et al. (2014), Cutter and Neidell (2009), and Henderson (1996) study how regulations and firm actions affect peaks in pollution (also known as 'episodic pollution' in this literature), but do not measure any health outcomes. Several additional papers document causal links between health and air pollution in unique experimental and quasi-random settings,[8] but the relevance of these relationships for realized exposure in daily life remains unclear. One notable exception is Hansman, Hjort, and León (2018), who find that a given amount of pollution exposure has larger health impacts when emitted over an extended period of time than when concentrated into a short-term period. The dearth of research on short-term exposure creates uncertainty for policy-makers around the optimal targeting of costly environmental regulations, for example, regulating peak hours versus annual average concentrations. Improving our understanding of these relationships is crucial for optimizing environmental regulations, especially if daily averages and transient peaks have heterogeneous health effects. The Environmental Protection Agency (EPA) National Ambient Air Quality Standards (NAAQS), for example, targets both 365-day averages and 1-hour peaks, which could have significant heterogeneity in both regulatory costs as well as economic costs and benefits (EPA, 2023).

This paper also contributes rigorous causal evidence to the ongoing policy debate around the global transition towards cleaner cooking technologies (Gill-Wiehl and Kammen, 2022). Extensive research has associated a wide range of health problems with energy-intensive cookstove usage, but most papers are correlational rather than causal, or focus on adoption rather than on the impacts of improved cookstoves.[9] A recent meta-analysis in *The Lancet* identified 437 studies on the health impacts of cookstoves: only six were randomized trials (Lee et al., 2020). The article identified an "urgent need for clinical trials evaluating cleaner fuel interventions on health outcomes to underpin evidence-based policy and decision making." Randomized studies on improved cookstoves often are limited to short-term outcomes, lack quantitative measurements of pollution exposure, or rely exclusively on self-reported health measures (Table 1 provides an overview of the causal evidence).

The large RESPIRE and HAPIN trials are valuable exceptions to this (T. F. Clasen et al., 2022; Smith et al., 2011), however these trials focus exclusively on rural communities. In a 2018 review of the cookstove literature, Thakur et al. (2018) identified no urban papers.[10] There is almost no evidence evaluating cooking exposure in contexts with high ambient pollution, even though the 1 billion urban poor who live in slums are simultaneously chronically exposed to both: 80% of urban

[7] See Clay, Lewis, and Severnini, 2022; Deryugina et al., 2019; Graff Zivin and Neidell, 2012; Greenstone and Hanna, 2014; Isen, Rossin-Slater, and Walker, 2017; Schlenker and Walker, 2015.

[8] See Adhvaryu, Kala, and Nyshadham (2022), Archsmith, Heyes, and Saberian (2018), Ebenstein, Lavy, and Roth (2016), Kubesch et al. (2015), Künn, Palacios, and Pestel (2023), Soppa et al. (2014), and Wen and Burke (2022).

[9] See Bensch, Grimm, and Peters (2015), Bensch and Peters (2019), Burwen and Levine (2012), Chowdhury et al. (2019), Levine et al. (2018), Miller and Mobarak (2013), Mobarak et al. (2012), and Pattanayak et al. (2019).

[10] More recently, Alexander et al. (2018) measured peak and duration of exposure to estimate the pollution and health impacts of improved stove adoption in an urban setting, but their sample is restricted to pregnant women, they do not separately measure ambient pollution, and they examine relatively modest variation in air pollution (a 5–13% reduction in peak—and no impact on mean—PM2.5).

African residents use biomass as their primary cooking energy (FAO, 2017). Papers that do evaluate the health impact of ambient air pollution in low- and middle-income countries (LMICs) rarely evaluate personal exposure.[11] Our findings furthermore depart from some earlier research asserting own-household generated air pollution plays a dominant role in aggregate pollution exposure (WHO, 2014; Fisher et al., 2021).

2 Air pollution and health

While domestic government PM2.5 regulations vary, most countries—as well as the WHO—only set standards on annual and 24-hour average concentrations. Russia also limits 20-minute average concentration, making it the only country that regulates a sub-24 hour average. A recent WHO Bulletin states, *"The current 24-hour standards mask sharp PM2.5 concentration spikes over short periods of minutes to hours. Jurisdictions with a high temporal variability of PM2.5 concentration, such as in India and China, should consider short-term averaging (such as over 20 minutes or 1 hour)"* (Nazarenko, Pal, and Ariya, 2021).

Whether to impose air pollution standards on shorter peaks is subject to ongoing policy debate, for example in the recent U.S. Environmental Protection Agency (EPA) evaluation of the National Ambient Air Quality Standards (NAAQS) for Particulate Matter (EPA, 2023). The lack of rigorous causal evidence on the health impacts of repeated short-term peaks hampers effective regulatory design. Most causal studies evaluating short-term air pollution peaks evaluate the impact of a single transient peak, whereas the relevant object for regulatory design is repeated exposure to peaks, which we are able to evaluate in this study.

One of the most common sources of short-term, transient air pollution peaks are indoor cooking events. Traditional charcoal cookstoves produce indoor air pollution that causes millions of deaths each year (WHO, 2017; Bailis et al., 2015; Pattanayak et al., 2019). More than 4 billion people still do not have access to modern cooking methods (WB, 2020). Table 1 presents an overview of experimental evidence studying the health impacts of improved cookstoves.

Three billion people are expected to live in slums in Africa and Asia by 2050, which experience unhealthy PM2.5 levels on a daily basis (WHO, 2021; UN, 2022). In Africa, 80% of households living in African cities still primarily use biomass (wood or charcoal) for cooking (FAO, 2017). As a result, urban LMIC residents suffer disproportionately from both ambient air pollution (AAP) and own household-generated (HAP), yet there is effectively no causal evidence assessing AAP and HAP simultaneously.

2.1 Cookstoves in Kenya

Two-thirds of Kenyan households rely on biomass (wood and charcoal) as their primary household fuel (KNBS, 2019; WB, 2019). Around 42 percent of Kenyan households use a Kenyan ceramic *'jiko'*

[11] See Adhvaryu, Kala, and Nyshadham (2022), Adhvaryu et al. (2023), Barrows, Garg, and Jha (2019), Ebenstein et al. (2017), Greenstone and Hanna (2014), and Gupta and Spears (2017).

Table 1: Experimental research on cookstove impacts

Authors	Year	Country	Urban	Pollution Monitored	Health Measure-ments	Months to Last Followup	House-holds
Berkouwer and Dean	2023	Kenya	Yes	PM, CO	Yes	42	702
RESPIRE trial papers							
McCracken *et al.*	2007	Guatemala	No	PM	Yes	10	537
Smith-Sivertsen *et al.*	2009	Guatemala	No	CO	Yes	18	534
Smith *et al.*	2011	Guatemala	No	CO	Yes	18	534
Thompson *et al.*	2011	Guatemala	No	CO	Yes	18	266
Romieu *et al.*	2009	Mexico	No	*None*	Yes	10	668
Burwen and Levine	2012	Ghana	No	PM, CO	No	8	488
Beltramo and Levine	2013	Senegal	No	PM, CO[b]	No	6	790
Alexander *et al.*	2014	Bolivia	No	CO	No	24	20
Jary *et al.*	2014	Malawi	No	PM, CO	Yes	0.25	50
Bensch and Peters	2015	Senegal	No	*None*	Yes	30	253
Tielsch *et al.*	2016	Nepal	No	PM	No	18	3376
Hanna *et al.*	2016	India	No	CO	Yes	48	2575
Mortimer *et al.*	2017	Malawi	No	*None*	Yes	24	8470
Alexander *et al.*	2018	Nigeria	Yes	PM, CO	No[a]	24	324
Checkley *et al.*	2020	Peru	No	PM, CO[b,c]	Yes	23	180
Adane *et al.*	2021	Ethiopia	No	PM	No	24	1977
Clasen *et al.*	2022	[d]	No	PM, CO[c]	Yes	18	3200

"Pollution Monitoring" refers to quantitative monitoring using a pollution monitoring device. "Health Measurements" refer to quantitative measurements, such as blood pressure, blood oxygen saturation, and spirometry (which are the most common among those with any quantitative measures). Pollution monitored includes particulate matter (PM) and carbon monoxide (CO). [a]While no health measurements are conducted, pregnancy outcomes are verified by hospital reports. [b]Also measures nitrogen dioxide (NO_2). [c]Also measures black carbon BC. [d]Four countries: Guatemala, India, Peru, and Rwanda.

for daily cooking, with the primary alternatives being wood stoves (in rural areas) and liquefied petroleum gas (LPG) and kerosene stoves (in urban areas) (Ministry of Energy, 2019). According to the World Bank's Kenya Country Environmental Analysis (2019), "Those who cook inside with poor ventilation have 400–600 $\mu g/m^3$ average annual concentration of PM2.5 in their household." These levels are extremely high: the WHO (2021) defines its 'healthy' threshold to be 5 $\mu g/m^3$. Furthermore, Pope et al. (2018) document that average PM2.5 and PM1.0 in Kenya are on average 2.8 times higher in urban roadside locations than in rural locations. They estimate urban roadside air pollution levels of 36.6 $\mu g/m^3$ and urban background levels of 24.8 $\mu g/m^3$.

Figure A1 displays a *jiko* as well as the Jikokoa, an energy efficient charcoal stove produced by Burn Manufacturing ('Burn'), which has sold more than two million energy efficient cookstoves since 2014. Berkouwer and Dean (2022a) provides more detail on charcoal consumption, barriers to adoption, and access to credit among potential adopters in Nairobi.

The primary difference between the Jikokoa and the *jiko* is that the Jikokoa's main charcoal combustion chamber is constructed using improved insulation material and designed for optimized fuel-air mixing. It is made of a metal alloy that better withstands heat, and a layer of ceramic wool insulates the chamber to cut heat loss. To maximize the charcoal-to-heat conversion rate, parts are made to strict specifications, and components fit tightly to minimize air leakage. These features were designed and tested by laboratories in Nairobi and Berkeley. Adoption of the energy efficient stove does not require any behavioral adaptation or learning as the cooking processes are identical. In line with lab estimates, Berkouwer and Dean (2022a) find that adoption of the Jikokoa reduces charcoal usage (as measured through charcoal expenditures and ash generation) by 39%. Most adopters continue cooking the same types and quantities of food as before, using the same type of charcoal.

2.2 Health measurement methodology

Our health-related outcome variables and the surveying methodology we use to measure them are informed by an extensive public health literature. Chang et al. (2015), Kubesch et al. (2015), and Soppa et al. (2014) document an association between air pollution and blood pressure within 1–2 hours of high pollution exposure. The Guatemala RESPIRE trial found impacts on blood pressure (McCracken et al., 2007), and more recently an experiment in urban Nigeria found that an improved stove can reduce blood pressure among pregnant women (Alexander et al., 2018). For children aged 5 and under, who are more likely than older children to spend more of their days with the primary cookstove user, frequent exposure to cooking-associated pollution may have negative health impacts, and for this reason our surveys include questions regarding adult and child health. Recent RCTs in rural Malawi and rural Guatemala found that improved stove adoption can reduce pneumonia in adults as well as in children (Mortimer et al., 2016; Smith-Sivertsen et al., 2009).

In settings where the technology to formally diagnose pneumonia is unavailable, the literature recommends three methodologies to diagnose pneumonia. The first is to inquire about diagnoses made by health professionals. The second is to ask about symptoms related to respiratory distress in order to make an attempted diagnoses of an acute respiratory infection (ARI), which can then be cautiously interpreted as a presumed pneumonia diagnoses. This methodology is standard for, among others, the World Health Organization, the USAID Demographic and Health Survey (DHS) program, and UNICEF.[12] Finally, oximetry readings have been found to be a cost-effective approach to screening for respiratory infections (Floyd et al., 2015; National Library of Medicine, 2021; Van Son and Eti, 2021).

One challenge when trying to identify the health impacts of improved stoves, experienced by for example Beltramo and Levine (2013) and Hanna, Duflo, and Greenstone (2016), is lack of stove usage. Berkouwer and Dean (2022a) rules this out in this paper's study context.

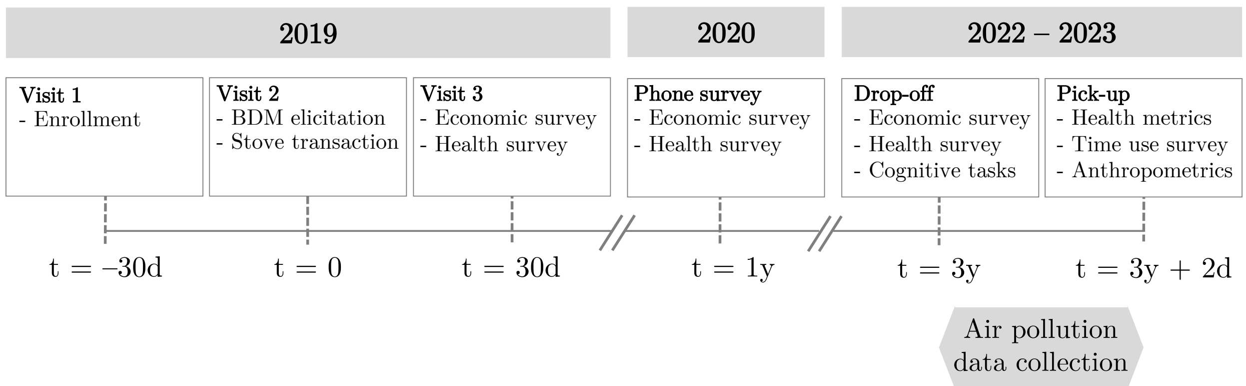
3 Study design and methodology

The study consists of three surveys conducted in 2019, a medium-term follow-up conducted in 2020, and a long-term follow-up conducted in 2022–2023. Figure 1 presents an overview of the study

[12] For example, UNICEF MICS6 (2020) identifies ARI if a child had fast, short, rapid breaths or difficulty breathing in combination with chest problems.

elements included in each survey round.

Figure 1: Timeline of field activities



Participants who adopted the stove did so during Visit 2 ($t = 0$). For 89% of respondents the long-term endline was conducted between 3.4–3.7 years after Visit 2. Cognitive tasks and anthropometrics of household members were collected on either drop-off or pickup depending on attendance. Due to COVID-19 related health restrictions, the 2020 follow-up survey was conducted over the phone.

In the initial baseline enrolment survey activity conducted in April-May 2019, enumerators enrolled respondents residing in urban settlement areas around Nairobi, Kenya who used a traditional charcoal stove as their primary daily cooking technology and who spent at least $3 per week buying charcoal. Within each household they enrolled the primary cookstove user. To elicit baseline levels of health, enumerators asked respondents whether they had experienced a persistent cough or breathlessness in the past week. If they had any children under 16 who lived with them, we asked the same about the child(ren). Enumerators then elicited beliefs about the potential health impacts of an improved stove using methodologies from the health literature (Hooper et al., 2018; Usmani, Steele, and Jeuland, 2017). Specifically, in an unprompted manner they asked respondents what they perceived to be the main benefits of the improved stove—62 percent stated 'reduced smoke' (95 percent said 'saving money'). They then asked several Likert scale questions about the extent to which the respondent thought usage of a traditional stove has had negative impacts on their health, and how much adoption of an energy efficient stove might improve their health.

The main visit—Visit 2, completed by 955 respondents—took place approximately one month after each respondent's baseline enrolment visit. During this visit, respondents received at least a $10 subsidy off the retail price and were able to buy the stove using the subsidy (Figure A2 shows the distribution of prices). Of the 955 respondents who completed the main visit, 570 (60 percent) adopted the Jikokoa stove.

In June–July 2019, approximately one month after the main visit, enumerators conducted a short-term endline survey. In 2020, enumerators conducted a medium-term survey.[13] These surveys ask about a range of socioeconomic outcomes, including charcoal expenditures, savings (in bank accounts, mobile money accounts, or rotating savings groups), as well as the same health symptoms questions asked during the baseline surveys.

[13] Due to COVID-19, all surveys conducted in 2020 were conducted over the phone.

Table 2: Summary statistics from respondent surveys

	N	Mean	SD	25^{th}	50^{th}	75^{th}
Female respondent	702	0.96				
Completed primary education	702	0.70				
Completed secondary education	702	0.26				
Age	702	41.46	11.8	33.0	40.0	48.0
Children under 5 in home	702	0.50	0.7	0.0	0.0	1.0
Daily earnings (USD)	563	2.77	5.8	1.0	1.7	3.1
Daily charcoal expenditure (USD)	702	0.48	0.6	0.2	0.3	0.6
Minutes spent cooking per day	702	127.54	59.5	90.0	120.0	150.0
... of which indoor	702	111.80	61.3	70.0	109.0	150.0
Owns Jikokoa	702	0.52				
Owns traditional wood or charcoal jiko	702	0.57				
Owns LPG stove	702	0.59				
Owns electric stove	702	0.01				
Mostly uses modern stove	702	0.53				
Blood oxygen	696	96.74	2.4	96.0	97.0	98.0
Average systolic blood pressure	696	123.46	22.0	108.3	118.5	131.7
Average diastolic blood pressure	696	81.75	12.9	73.0	79.3	89.0
Number of health symptoms	702	2.47	2.6	0.0	2.0	4.0
In the past month, have you experienced...						
Fever	702	0.22				
Headache	702	0.48				
Persistent cough	702	0.23				
Runny nose	702	0.22				
Sore throat	702	0.15				
Always feeling tired	702	0.28				

Standard deviation and 25^{th}, 50^{th}, 75^{th} reported for all non-binary variables. Blood pressure is averaged over three readings taken consecutively.

In 2022-2023 enumerators conducted a long-term survey round, which consisted of two surveys, the second approximately 48 hours after the first. The surveys were designed to take quantitative measurements of three long-term outcomes: air pollution, physical health, and cognition. An accompanying socioeconomic survey included questions on charcoal expenditures, cooking technology ownership and usage, maintenance, food cooked, home heating, in-network Jikokoa purchases, savings, income, and work activities. Table 2 presents summary statistics. Enumerators were able to reach 775 of the 942 respondents they attempted to reach, and successfully surveyed 702 (75%).[14]

[14] 13 of the 955 respondents completed the main visit in 2019 but removed themselves from the study between 2019 and 2022. 167 respondents could not be contacted in 2022-2023 despite repeated phone calls to their phone numbers or any other phone numbers they had used for earlier SMS surveys or MPESA payments. Physical attempts to track individuals residing in the study areas were hampered by the recent demolitions of housing in Nairobi's settlement areas (The Star, 2023). Respondents who were contacted but who did not complete a 2022-2023 survey did not do so for various reasons, including nonconsent, migration, physical incapacitation, or death. As a rule we attempted to

95% of respondents were surveyed between 3.4–3.7 years after the original main visit.

To match high-frequency pollution data to specific activities, the second survey included a time use module inquiring about which activities the respondent was engaged in for each hour between the two surveys, whether they were indoors or outdoors during each hour, and if they were cooking, which stove(s) they were using. Most respondents cook primarily between the morning hours of 5–8am and the evening hours of 6–9pm. There are modest differences in the types of technologies used during different types of day, with LPG used more in the mornings and a charcoal jiko or Jikokoa used more in the evenings (Figure A3). [15]

The time use data indicate that households primarily cook indoors: 89% of time spent cooking takes place indoors, on average. Improved cookstove adoption does not meaningfully affect the propensity to cook indoors (Table A9). However, there is some heterogeneity in behavior correlated with stove usage. For the 278 households who report using an LPG or electric stove at least once in the time use survey, on average only 5% of the time spent cooking with such a stove is spent outdoors. Conversely, for the nearly 500 households who report using a wood or charcoal stove at least once in the time use survey, more than 20% of time spent cooking with such a stove is spent outdoors. It is plausible that respondents are more likely to choose to cook indoors when using a relatively cleaner stove, and that this reduces the benefits of an improved stove, as emissions are more likely to build up when cooking indoors. Our results should be interpreted as factoring in relevant behavior changes such as location choice, or opening doors or windows in order to increase household ventilation rates.

3.1 Causal identification

After completing the initial baseline enrolment survey, each respondent was randomly assigned a subsidy of between $10-39 for the energy efficient Jikokoa stove, which cost $40 in stores at the time. The random assignment of subsidies was stratified on baseline charcoal usage. The subsidy assignment was cross-randomized with a random credit treatment allowing recipients to pay for the stove in installments over a 3-month period, as well as an attention treatment designed to increase the salience of long-term charcoal savings.

During visit 2, enumerators used a Becker, Degroot, and Marschak (1964) mechanism (BDM) to elicit WTP for the Jikokoa stove. After first identifying their maximum WTP through a binary search, respondents then opened an envelope containing their randomly assigned price. Respondents whose WTP was at least as high as their randomly assigned price (the market price of $40 minus the randomly assigned subsidy) then adopted the stove.[16]

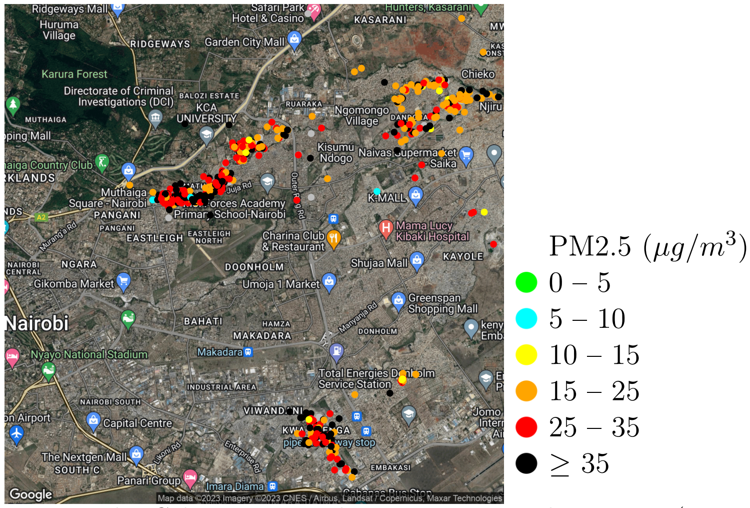
The credit treatment doubled WTP, while the attention treatment had no effect on WTP (Figure A4 shows the full WTP distributions by treatment group). The randomized credit and subsidy

survey any respondent still residing in Kenya. Attrition is balanced by treatment assignment, take-up, and baseline health (Table A23).

[15] Anecdotally, this is due to a preference for a fast-lighting stove (which the LPG stove is, in comparison to biomass) in the morning, for a small meal or hot beverage, and a longer-cooking stove when preparing larger meals.

[16] 98.6% of respondents who 'won' the stove through the BDM actually adopted the stove.

Figure 2: Average air pollution (PM 2.5) for participants by their home locations



Distribution of respondents across Nairobi. Colors correspond to average particulate matter (PM 2.5) exposure. Respondents for whom pollution was not recorded are shown in gray. The WHO air quality guideline (AQG) is 5 $\mu g/m^3$ (WHO, 2021). WHO interim targets 1 through 4 correspond to 10, 15, 25, and 35 $\mu g/m^3$. Some respondents were surveyed outside the visible area.

treatments were highly predictive of improved stove adoption: among those in both the high subsidy and the credit treatment group 93% adopted the Jikokoa, whereas among those in both the low subsidy and the credit control group only 8% did. To estimate the causal effect of improved stove adoption on long-term outcomes we use the randomly assigned subsidy, the credit treatment assignment, and their interaction as instruments for adoption. We report weak instrument F-statistics where relevant—the first stage is generally strong.

3.2 Air pollution exposure concentrations

We use two different devices to measure air pollution. A Purple Air II Air Quality Sensor (PA-II) takes one measurement of Particulate Matter (PM) every two minutes (Panel A of Figure A5),[17] and a Lascar EL-USB-CO Data Logger takes one measurement of Carbon Monoxide (CO) per minute (Panel B of Figure A5).[18] A test of co-located readings shows that devices are strongly correlated and that there is a small and generally stable gap between some devices (Figure A6). For this reason we include device fixed effects in all regressions.[19] Figure 2 maps respondents' interview locations and average air pollution exposure.[20]

Air pollution exposure varies considerably not only by cookstove usage but by the user's behavior

[17] We average the PA-II a and b readings, and top-code data at 419 $\mu g/m^3$ above which the device saturates. We apply the PA-II calibration methodology from Giordano et al. (2021) and Ward et al. (2021) to correct for humidity and local air composition. Building on Tryner et al. (2020), if the difference between the a and b readings is at least 25% and at least 15 $\mu g/m^3$ the reading is removed from the sample (1.7% of readings).

[18] Each CO device has an independent calibration factor. Devices were re-calibrated every two months, between survey breaks. We include device FE in all regressions.

[19] Interacting device fixed effects with a linear time trends could account for heterogeneous trends across devices. Doing so introduces noise and therefore increases standard errors, but does not qualitatively change the results.

[20] 60 survey respondents were located elsewhere in Nairobi or in rural areas (not shown in Figure 2).

around cooking practices (Pitt, Rosenzweig, and Hassan (2010) discuss how household structures affect exposure). Following best practices (Gordon et al., 2014; Gould et al., 2022), we designed the deployment methodology to collect exposure as experienced by respondents rather than stationary monitoring of kitchen concentrations. Collecting pollution exposure over a 48-hour period captures HAP as well as AAP generated by industrial facilities, traffic, or other sources in urban Nairobi.

To achieve this, we used procedures developed by the Berkeley Air Monitoring Group (Johnson et al., 2021). During the first endline survey we provided each respondent with a small mesh backpack containing the two devices (Panels C and D of Figure A5). 48 hours later the enumerators then picked up the devices, downloaded the data, recharged the 48-hour battery pack, and placed them in a new backpack to be deployed with a different respondent.[21] Respondents were asked to wear this backpack continuously whenever feasible, or to keep it within one meter, at waist level, when wearing it was infeasible. We did not quantitatively monitor backpack wearing, as this would have required installing GPS trackers on the backpacks which we felt could be perceived as violating participants' privacy and increase attrition. However, qualitatively, enumerators reported generally high backpack wearing.[22] Our methodology is in line with best practices from the air pollution monitoring literature (Burrowes et al., 2020; Chillrud et al., 2021; Gould et al., 2023).

One concern with deploying conspicuous sensors is that respondents may be more self-conscious of their own cookstove usage and alter their cookstove use in response, biasing our estimates—a concern known as the Hawthorne effect. Existing research has identified this effect in the monitoring of health technologies such as cookstoves or latrines (e.g. T. Clasen et al., 2012; Simons et al., 2017). For this reason we administer questions about charcoal expenditures and cookstove usage during the first survey, before deploying the devices.

To better understand peak pollution patterns we compute average exposure during each 10-minute window for each respondent in our data. Panel B of Figure 3 shows the cumulative distributions of each respondent's 50th (median) and 99th percentile 10-minute average, with the 99th percentile 10-minute average representing approximately the worst 15 minutes of one's day. Median 10-minute average is below 50 $\mu g/m^3$ for 89% of respondents. However, the worst 15 minutes of the day is above 100 $\mu g/m^3$ for half of respondents, and exceeds 200 $\mu g/m^3$ for 23% of respondents.

Panel A of Figure 3 presents average pollution over the hours of the day by whether or not the respondent owned a Jikokoa. The levels and diurnal patterns of PM2.5 and PM1.0 follow the air pollution patterns documented by Pope et al. (2018) in urban Kenya. We do not observe any meaningful seasonal heterogeneity in air pollution over our sample period. Matching hourly time use data and hourly pollution data indicates that PM2.5 is lowest in the hours when sleeping (32 $\mu g/m^3$) and highest in the hours when cooking (46 $\mu g/m^3$) on average (Table A1). Similarly,

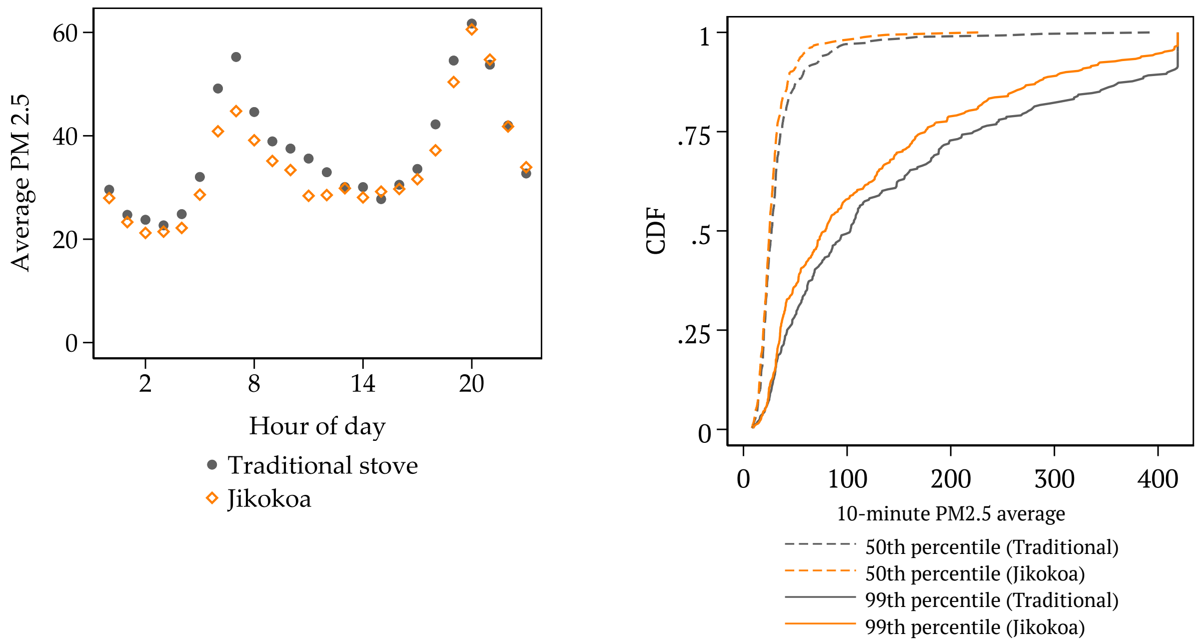
[21] 85% of respondents held the device between 45–50 hours. Air pollution data are missing for 45 respondents who only had time to complete a single survey.

[22] Enumerators were attentive to this: for example, they raised concerns about a lack of continuous backpack wearing as respondents would take off the backpack for example while sleeping it (placing it next to their beds) or while working statically (placing it on a table), which we agreed was acceptable as long as the backpack was within one meter of the respondent. That enumerators were attentive enough to identify this issue suggests they likely would have noticed any widespread more severe non-compliance.

Figure 3: Particulate matter (PM2.5, in $\mu g/m^3$) pollution by Jikokoa ownership

A) Over the hours of the day

B) Distributions of 50th and 99th percentiles of 10-minute averages (by household)



Panel A shows average PM2.5 air pollution, by hour and endline Jikokoa ownership, as collected by respondents wearing backpacks for on average 48 hours. Figure A7 presents the same for PM1.0 and CO.

correlations between PM2.5 and CO exposure and time use categories suggest exposure increases while cooking, especially when using biomass fuel stoves (Table A5).

3.3 Physical health

Enumerators record systolic and diastolic blood pressures using a sphygmomanometer, following procedures set by the Centers for Disease Control and Prevention NHANES (2019).[23] The analysis uses direct measures of systolic and diastolic blood pressure as well as indicators for having hypotension (low blood pressure, defined as <90/60 mmHg), stage 1 hypertension (130-139/80-89 mmHg), and stage 2 hypertension ($\geq$ 140/$\geq$ 90 mmHg), as defined by the American Heart Association and the American College of Cardiology (Goetsch et al., 2021). Enumerators use pulse oximeters (blood oxygen saturation monitors) to record haemoglobin oxygen saturation.[24]

The survey furthermore asks a large set of health questions, following the methodology from field experiments in the public health literature (see for example Checkley et al., 2021; Smith-Sivertsen et al., 2009; Tielsch et al., 2016 and others). This includes a set of 10 yes/no questions asking

[23] Respondents are asked to sit still, upright, and not engage in affecting behaviors (cooking, smoking, etc.) in the 30 minutes prior to the blood pressure readings. In line with guidelines, blood pressure is recorded three times and the analysis uses the average of the three readings.

[24] While we considered collecting spirometry or peak expiratory flow data, discussions with medical consultants in Kenya and the U.S. suggested that these run the risk of generating noisy and unusable data. We therefore chose to focus on improving the quality of the personal exposure, blood pressure, and blood oxygen measurements.

if a medical professional had diagnosed the respondent with various medical diagnoses (including pneumonia, asthma, or other lung disease), of which we only keep diagnoses that were made in the past three years (since the original experiment). It includes a set of 29 yes/no questions asking if the respondent experienced specific symptoms in the past 4 weeks (including fever, persistent cough, stomach pain, or rapid weight loss, as well as symptoms required to make a presumed pneumonia diagnosis). The survey also asks about perceptions of health impacts, and frequency and financial costs of hospital visits. For female respondents, the enumerator also inquired about recent pregnancies, birth outcomes, and any recent newborns' weight and length. We use these self-reports to generate several standardized adult physical health indices.

The adult respondent is asked similar questions about symptoms any children under 10 who live in the home, including questions about overall health, basic health symptoms (specifically those that permit a presumed pneumonia diagnoses, including fever, vomiting, and cough), school attendance, and medical diagnoses. Subsets of these are then combined into several standardized child physical health indices. The enumerator finally measured child and adult height, weight, and arm circumference as indicators for physical child development and for parental controls, respectively.

17% of respondents report having been diagnosed with pneumonia by a doctor at least once in their lives, including 12% who report having been diagnosed in the past three years. Table 2 presents additional summary statistics on health outcomes. To control for diurnal patterns in health outcomes such as blood pressure, health regressions control for the hour of day during which each survey was administered.

3.4 Cognition

To assess basic adult and child cognitive functions, we use three instruments. First, we use the Reverse Corsi Block task to measure working memory (Brunetti, Del Gatto, and Delogu, 2014). Second, we use Hearts and Flowers to measure response inhibition (Davidson et al., 2006). Third, we use the d2 task for sustained attention (Bates and Lemay Jr., 2004; Brickenkamp and Zillmer, 1998). Appendix C provides detail on these assessments. The analysis uses a standardized adult cognitive ability index.

4 Causal impacts

To estimate the causal effect of adoption of the energy efficient charcoal cookstove on pollution, health, and socioeconomic outcomes, we employ an instrumental variables (IV) approach where we use the randomly assigned BDM price, the randomly assigned credit treatment status, and their interaction as instruments for stove ownership. These were the two random treatments found to have a statistically and economically large effect on stove adoption in Berkouwer and Dean (2022a).[25] Since both are randomly assigned, this regression identifies the causal effect of stove adoption on the outcomes of interest.

[25] We omit a third random treatment, attention to energy savings, as it had no impact on adoption.

As appropriate, regressions include socioeconomic controls[26] and panel data fixed effects.[27] Note that 'stove adoption' could represent either initial adoption in 2019, or ownership status as of the 2022–2023 endline survey. Using initial adoption represents the longer-term effects of adoption, factoring in potential breakage or other subsequent changes in stove ownership, but underestimates contemporaneous effects as some treated individuals are no longer benefiting from the treatment. Long-term adoption status better estimates contemporaneous differences, but could result in an overestimated IV coefficient if changes experienced by respondents who initially adopted the stove but no longer own one at endline are attributed to the (smaller) treatment group. We present both estimates where relevant but use ownership as of the long-term follow-up in most regressions.

4.1 Impacts of random treatments on stove ownership and usage

Panel (A) of Table 3 shows the causal impact of 2019 Jikokoa adoption on long-term ownership of various stove types. 90% of respondents who did not adopt a Jikokoa during the main visit also do not own one during the long term endline, and 83% of respondents who adopted a Jikokoa initially also own one three years later. This persistence generates a strong first stage to study the impacts of the Jikokoa on other outcomes, with weak IV F-statistics between 20 and 50 depending on the specification (Table A2 presents the first stage).

The median household owns two unique stove types, indicating some degree of 'fuel stacking' (simultaneous ownership of cooking technologies that use multiple types of cooking fuel). LPG ownership has risen sharply in recent years, with 57% of respondents reporting owning an LPG stove, potentially as a result of a government LPG subsidy program (IEA, 2022). The estimates should be interpreted as the aggregate causal effect of improved cookstove adoption, allowing for any continued use of existing stove (rather than an estimate of a strict switch from an existing stove to an improved stove).

Jikokoa adoption does not appear to meaningfully affect adoption of other modern cooking technologies such as liquefied petroleum gas (LPG), bio-ethanol, or electric stove ownership, though we cannot rule out modest increases. We thus find limited evidence of the 'energy ladder' mechanism whereby initial adoption of an improved biomass stoves can act as a stepping stone towards even cleaner cooking technologies (Hanna and Oliva, 2015), nor of the converse, that adoption of an intermediary technology can slow adoption of a more energy efficient technology (Armitage, 2022). Stove adoption slightly increases a user's propensity to cook githeri (a common Kenyan dish consisting of maize and beans) but has no impact on the propensity to cook any other food types (Table A11).

[26] Socioeconomic controls used in each regression are the respondent's attention treatment status (a treatment designed to increase attention to energy savings), age, gender, savings in 2019, income in 2019, number of residents in the household in 2019, number of children in the household in 2019, prevalence of a cough or breathlessness at night in 2019, hours of work/homework missed due to poor health, education level completed in 2019, charcoal expenditures in 2019, level of risk aversion in 2019, status of credit constraint in 2019, living situation as rural or urban, age as decade binary variables (designed to capture non-linear impacts of age), as well as field officer fixed effects.

[27] Panel data fixed effects include week FE, device FE, and the interaction of and hour-of-day by day-of-week by neighborhood FE.

4.2 Impacts of stove ownership on air pollution

The relationship between stove ownership and air pollution varies significantly across hours in the day. Panel (A) of Figure 4 presents a standard OLS panel fixed effects regression, estimating a separate coefficient for each hour of the day. Panel (B) uses the IV approach to similarly estimate a separate causal estimate for each hour of the day. For comparability, both panels also present a histogram of the number of people who reported cooking during a given hour in the time use

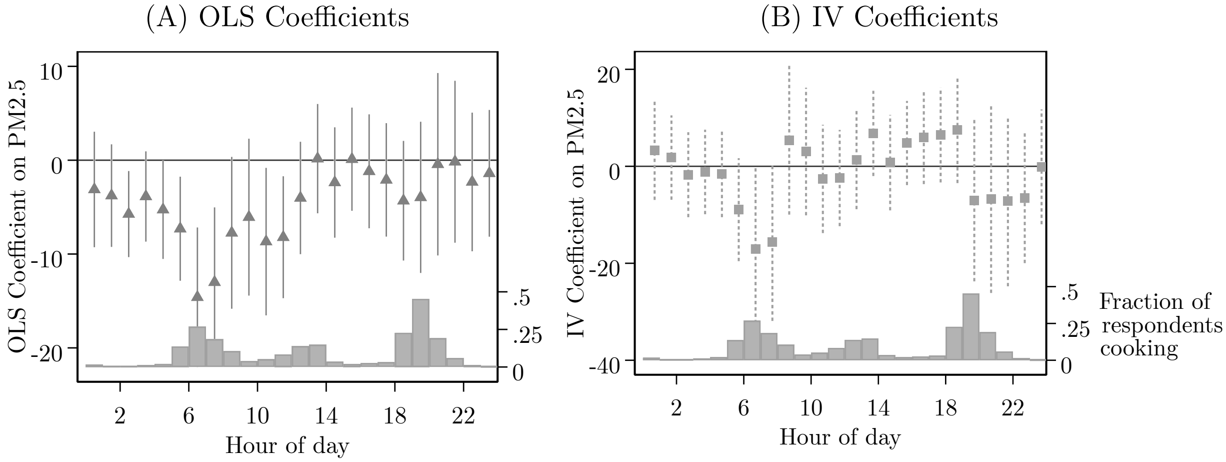
Table 3: Primary socio-economic outcomes

	Control Mean (1)	Treatment Effect (2022 Ownership) (2)	Treatment Effect (2019 Ownership) (3)	N
Panel A				
Owns other wood or charcoal stove	0.88		-0.54***	702
	[0.33]		(0.05)	
Owns Jikokoa	0.10		0.74***	702
	[0.31]		(0.04)	
Owns LPG stove	0.57		0.05	702
	[0.50]		(0.06)	
Owns bio-ethanol stove	0.15		0.01	702
	[0.36]		(0.04)	
Owns electric stove	0.00		0.02*	702
	[0.06]		(0.01)	
Panel B				
Charcoal expenditures past 7 days (USD)	3.65	-1.50***	-1.12***	702
	[2.93]	(0.47)	(0.35)	
Charcoal expenditures past 7 days (urban)	3.79	-1.65***	-1.20***	649
	[2.94]	(0.52)	(0.37)	
Charcoal expenditures past 7 days (rural)	1.82	1.22	1.16	53
	[2.09]	(1.00)	(0.81)	
Hours worked past 2 weeks	65.25	-3.23	-2.71	702
	[60.87]	(11.04)	(8.16)	
Earnings past 2 weeks (USD)	32.20	4.73	3.45	563
	[35.31]	(7.83)	(5.38)	
Total savings (USD)	57.70	-8.63	-7.07	701
	[94.87]	(19.88)	(14.67)	
Has formal bank account (=1)	0.12	0.11	0.08	702
	[0.33]	(0.07)	(0.05)	
Minutes cooking per day	133.79	3.49	2.60	702
	[57.29]	(8.32)	(6.15)	
People in network who adopted Jikokoa	0.75	1.13***	0.84***	702
	[2.03]	(0.40)	(0.29)	

Panel A presents the causal impact of 2019 Jikokoa adoption on 2022–2023 cookstove ownership. Panel B presents the causal impact of 2022 Jikokoa ownership and 2019 Jikokoa adoption (Columns 1 and 2 respectively) on outcomes recorded during the 2022–2023 endline surveys. Each row is an IV regression that uses the randomly assigned price, credit treatment status, and their interaction as instruments for the endogenous variables. Regressions include socioeconomic controls. Table A3 presents additional socio-economic outcomes relating to savings and in-network adoptions.

survey. Improved stove ownership reduces air pollution between 5–8am, which lines up well with when respondents generally report to be cooking breakfast.

Figure 4: Impact of Jikokoa ownership on average hourly PM2.5 (in $\mu g/m^3$)



Panel (A) reports coefficients from an OLS regression of PM2.5 on Jikokoa ownership. Panel (B) reports coefficients from an equivalent IV regression, using subsidy, credit treatment status, their interaction, and their interaction with hour of day dummies as instruments. Both regressions include socioeconomic controls and panel data fixed effects. The gray bars report the fraction of respondents who report cooking during any given hour in the time use survey. Table 4 presents regressions pooling data across respondents, for PM2.5 (Panel A) and CO (Panel B).

Figure 4 also reveals a modest reduction in air pollution concentrations during dinnertime between 7–9pm, though this reduction is significantly smaller than the effect during breakfast time. The lack of effect during dinnertime is not driven by differences in cooking technologies used during the different meals: during all daytime hours, a Jikokoa is being used by approximately 30% of respondents that are cooking, a traditional Jiko by approximately 27%, and an LPG stove by approximately 23% (Figure A3). There is a slight difference in temperature, with a 10^{th}–90^{th} percentile range of 26–33°C between 5–7am and 29–36°C between 7–9pm (according to the PA-II devices), however this difference is sufficiently small that it is unlikely to account for the differences in treatment effects we see. Instead, we hypothesize that the lack of reduction in dinnertime pollution exposure is due to diurnal variation in planetary boundary layer height (PBLh). A lower PBLh weakens the exchange of air between the earth's boundary layer and the free atmosphere, trapping particles closer to earth's surface. NASA MERRA-2 satellite measurements indicate that PBLh in Nairobi is on average 1,600 meters during the morning hours of 5–8am but on average 60 meters during the evening hours of 7–9pm (Figure A8). Previous research has documented a strong relationship between PM2.5 and PBLh (Dhammapala, 2019; Dobson et al., 2021; Manning et al., 2018). Low PBLh during the evening may saturate the boundary layer and reduce the marginal impact of cookstove emissions reductions, but more research is needed to confirm this channel.

Table 4 aggregates pollution exposure data for each individual and estimates the causal impact of stove adoption on three key moments of pollution exposure, following the same IV approach. Columns (1) and (5) estimate the causal impact on median exposure while Columns (2) and (6) estimate the causal impact on mean exposure, taken over all (minute- or 2-minute level) readings.

Table 4: Causal impact of cookstove adoption on pollution exposure

Panel A) All hours

	PM2.5				CO			
	(1) Median	(2) Mean	(3) Max Hour	(4) 99th	(5) Median	(6) Mean	(7) Max Hour	(8) 99th
Own Jikokoa	0.1	-0.8	-16.4	-8.3	-0.5	2.2	21.5*	25.6*
	(1.7)	(3.4)	(19.0)	(23.0)	(0.4)	(1.7)	(12.8)	(15.1)
Control Mean	25.2	37.8	153.3	200.3	1.8	6.5	49.6	61.6
Weak IV F-Stat	53	53	53	53	52	52	52	52
Observations	651	651	651	651	656	656	656	656

Panel B) When self-reporting cooking

	PM2.5				CO			
	(1) Median	(2) Mean	(3) Max Hour	(4) 99th	(5) Median	(6) Mean	(7) Max Hour	(8) 99th
Own Jikokoa	-11.0**	-16.6***	-31.0**	-52.0**	1.1	1.4	8.3	6.2
	(5.2)	(6.4)	(15.4)	(22.5)	(2.1)	(3.1)	(9.9)	(14.2)
Control Mean	35.9	49.7	92.6	150.3	4.2	9.2	25.3	41.3
Weak IV F-Stat	48	48	48	48	47	47	47	47
Observations	598	598	595	598	609	609	608	609

Each column is an IV regression where the randomly assigned price, credit treatment status, and their interaction are used as instruments for endline Jikokoa ownership. Columns (1) and (5) use median exposure, (2) and (6) use mean exposure, (3) and (7) use maximum 1-hour average exposure, and (4) and (8) use 99th percentile of 10-min average exposure. Of the 702 respondents surveyed, 656 consented to having at least one air pollution monitoring device (Section 4.6 discusses attrition), and some of these never self-reported cooking. Regressions include socioeconomic controls and a fixed effect for the specific LASCAR or PA-II device used for that respondent. Table A7 presents the same for when self-reporting not cooking as well as for the hours between 6–8am and 6–9pm specifically, which is less prone to recall bias. Table A6 presents all four outcomes in logs.

Columns (3) and (7) consider the maximum of hourly average exposure while Columns (4) and (8) consider the 99th percentile of 10-minute averages. Panel A considers the full 45–50 hours during which the respondent was wearing the device, while Panel B limits the data to the hours during which the respondent self-reported cooking in the time use survey (Table A7 also presents results on all non-cooking hours and on cooking hours defined uniformly as 6–8am and 6–9pm, when most respondents report cooking).

Two key patterns emerge. First, there is a large and statistically significant reduction of 52 $\mu g/m^3$ in the 99th percentile of 10-minute means while cooking (Column 4 of Panel B), which corresponds to around a 40% reduction in the marginal emissions increase from cooking (over median non-cooking exposure) when compared with the control group. In other words, Jikokoa reduces the peak emissions from cooking by around 40%, which closely matches the 41% reduction in charcoal expenditures identified in Table 3. PM2.5 emissions from cooking appear to decrease approximately linearly in proportion to charcoal usage. These patterns are economically and statistically similar when the data are analyzed in logs (Table A6).

Improved cookstove adoption also reduces the time spent cooking (Column (1) of Table A8); anecdotally this is likely driven by the fact that the improved stove takes less time to heat up. As a result, the reduction in pollution in maximum hourly average is even larger—48%—as this factors in both the reduced peak levels as well as a reduction in the time spent near the stove during the most polluted cooking hour (Column 3 of Panel B in Table 4). We see no impact on the propensity to cook indoors (Table A9).

Second, however, there are no detectable effects on any of the other hours of the day, when ambient pollution remains high (Panel B of Table A7). As a result, despite large emissions reductions during cooking, there is only a 2% reduction in aggregate average exposure, and it is not statistically significantly different from zero (Column 2 of Panel A in Table 4). The lack of impact on aggregate average air pollution can be reconciled with the relatively small amount of time spent cooking daily: respondents cook for 9% of the day (2 hours) on average. Median non-cooking exposure to PM2.5 is around 25 $\mu g/m^3$. Indeed, we cannot reject that the coefficient in Column (2) of Panel A is 9% of that reported in Column (2) of Panel B. In this context, the reduction in cooking-related pollution causes only a small and statistically undetectable reduction in total pollution exposure.

Cooking hours are non-uniformly distributed across the day. Using hourly data on self-reported cooking activity and pollution allows us to include hour-of-day fixed effects in the regressions. This is in some ways preferred as it accounts for spurious correlations between diurnal patterns in pollution and in cooking. However we lose significant variation since there is indeed significant correlation between hour of day and propensity to be cooking. We estimate this regression using both IV and OLS specifications (Table A8). While the IV estimates are noisier than the OLS estimates, the results present a similar story: improved stove adoption does not affect PM during non-cooking hours but reduces average PM2.5 by around 8 μg/m^3 (and PM1.0 by around 4 μg/m^3) during cooking hours. To factor in that adoption reduces the time spent cooking, we conduct a complementary analysis of pollution during 'cooking hours', which we define as 6-8am and 7-9pm following Figure 4. In line with the results above, improved cookstove ownership causes an environmentally and statistically large reduction in average PM2.5 air pollution during cooking hours. However, as with the individual-level results, the high ambient pollution levels dampen any impact on aggregate exposure.

We can conduct a back-of-the-envelope exercise to get a sense for what pollution exposure reduction might be in rural areas, where ambient air pollution is 9 $\mu g/m^3$ (Pope et al., 2018). Even conservatively supposing that participants cook for twice as long in rural areas as in urban areas, this would still only generate a 22% reduction in aggregate exposure.[28]

Columns (5)–(8) of Table 4 indicate no impacts on CO. This is in line with recent independent laboratory tests scoring the Jikokoa Tier 3 for PM2.5 but Tier 1 for CO (CREEC, 2022). A stove's CO output generally depends on its rate of oxygenation: higher oxygen inflow increases the production of CO_2 and reduces the production of CO while cooking. Per the company's engineers,

[28] Unfortunately we are unable to use our own study data for this. Due to logistical surveying constraints in rural areas, most study participants residing in rural areas did not receive air pollution monitoring devices.

Table 5: Primary health outcomes

	Control Mean (1)	Treatment Effect (2022 Ownership) (2)	Treatment Effect (2019 ownership) (3)	N
Physiological health index (blood oxygen and blood pressure)	-0.00	0.02	0.02	696
	[1.00]	(0.17)	(0.13)	
Number of non-respiratory health symptoms	1.09	-0.24	-0.18	702
	[1.54]	(0.25)	(0.19)	
Non-respiratory health symptom index	-0.00	-0.03	-0.03	702
	[1.00]	(0.19)	(0.14)	
Number of respiratory health symptoms	1.70	-0.48**	-0.36**	702
	[1.76]	(0.23)	(0.17)	
Respiratory health symptom index	-0.00	-0.24*	-0.18*	702
	[1.00]	(0.13)	(0.10)	
Health diagnoses index	0.00	0.13	0.10	702
	[1.00]	(0.16)	(0.12)	
Number of health diagnoses	0.30	0.13	0.10	702
	[0.58]	(0.09)	(0.07)	
Cognitive index	-0.00	-0.01	-0.02	587
	[1.00]	(0.15)	(0.12)	
Healthcare utilization index (spending and visits)	0.00	0.08	0.05	702
	[1.00]	(0.14)	(0.11)	

Each row is an instrumental regression wherein endline modern stove use is instrumented for with randomly assigned price, credit treatment status, and their interaction. Regressions include socioeconomic controls and control for hour of day of the second visit, where blood pressure and blood oxygen were recorded. Table 6, Table A12, Table A13, Table A14, Table A15, and Table A16 present detailed results on the components of the physiological, symptoms, diagnoses, cognitive, and healthcare utilization indices. Outcomes for children are presented in Table A17.

the lack of reduction in CO output results from a desire to increase the durability of the stove by limiting peak cooking temperatures to 700°C. While this improves durability, it limits oxygenation.

It is worth noting that inverting these statistics to be represented as time above thresholds (for example, 'minutes per day where a participant is exposed to PM2.5 in excess of 100 $\mu g/m^3$') dramatically reduces the power of the estimation, as big changes that happen entirely below or entirely above the threshold will be ignored and only movements across the threshold will generate a treatment effect (Table A10). When trying to answer regulatory or health questions, looking at averages or other moments in the distribution can often generate more precise statistical results than relying on data on thresholds.

4.3 Impacts of stove ownership on health

Table 5 presents the primary estimates of the impact of stove adoption on health outcomes, using the IV approach discussed above and controlling flexibly for age and linearly for other socioeconomic outcomes measured at baseline. Column (2) uses 2022 Jikokoa ownership as the endogenous variable while Column (3) uses 2019 Jikokoa adoption as the endogenous variable.

The first outcome is an index of quantitative health measurements, while the next six outcomes are indices and counts of self-reported health outcomes. Following our pre-analysis plan (Berkouwer and Dean, 2022b) we separate self-reported health symptoms into those related to the respiratory system and those not. Table 6 presents the impacts of stove adoption on the components of the quantitative health measurement index.

Table 6: Physiology outcomes

	Control Mean	Treatment Effect	N
Average systolic blood pressure	122.16	0.49	696
	[18.97]	(3.30)	
Average diastolic blood pressure	81.32	0.58	696
	[11.73]	(2.15)	
Hypertension: Stage 1 or higher (>130/80)	0.51	0.02	696
	[0.50]	(0.09)	
Hypertension: Stage 2 or higher (>140/90)	0.27	-0.02	696
	[0.44]	(0.08)	
Blood oxygen	96.61	0.31	696
	[2.53]	(0.37)	

Each row is an instrumental variables regression where the randomly assigned price, credit treatment status, and their interaction are used as instruments for endline Jikokoa ownership. Regressions include socioeconomic controls.

The results indicate a 0.24 standard deviation reduction in self-reported symptoms directly related to pollution, such as sore throat, headache, and cough (Table A12 present more detailed results on pollution-related symptoms). Section 4.6 presents evidence for why these results are unlikely to be driven by experimenter demand (see Section 4.6 for more detail).

However, we identify no long-term health improvements in quantitatively measured outcomes such as blood oxygen and blood pressure, self-reported non-respiratory symptoms, and self-reports about any diagnoses made by a medical professional during a hospital visit (Table A13 and Table A14 present more detailed results on non-pollution related symptoms and medical diagnoses, respectively). Specifically, we can reject that owning a stove in 2019 decreased our diagnoses index by more than 0.14 SD and that it increased our physiological health index (composed of blood pressure and pulse oximetry) by more than 0.27 SD. In order to understand what this means clinically, it's useful to focus on the systolic component where we can reject a decrease of 5.97 mm Hg. Ettehad et al. (2016) conducted a metanalysis of 123 randomized controlled trials examining the health impacts of reducing systolic blood pressure. They find a 10 mm Hg reduction is associated with a 20% reduction in the risk of a major cardiovascular event off a base of 11%. Applying this estimate to our results suggests we can reject a change large enough to reduce major cardiovascular events by 12%. Similarly, we find no effect on the number of hospital visits, hospital-related expenditures, or any of the cognition outcomes (Table A15).[29]

These results point to important heterogeneity in the impacts of pollution exposure on health.

[29] Due to a technical issue with the tablets the sample size for some of the cognition outcomes is smaller than in other outcome tables. Since this was a technical issue, and since the order of follow-up surveys was randomized, it is unlikely that this biased the results in any meaningful way.

The significant reduction in intense, short-term peaks likely contributed to the reduction of self-reported and largely transient health symptoms. At the same time, the lack of reduction in aggregate average pollution exposure may explain the lack of impacts on chronic or quantitative health outcomes, despite 3.5 years of sustained use of reduced peaks in air pollution. Taken together, this suggests that while reductions in peak exposure can generate important short-term health improvements, improvements in long-term measures of health may require reductions in ambient air pollution exposure. Section 5 explores the direct link between pollution exposure and health in more detail.

We cannot detect a statistically significant impact on a range of child health outcomes, including weight, height, and arm circumference, a range of self- or parent-reported symptoms, and two types of attempted pneumonia diagnoses (Table A17), neither among children under 10 nor when restricting the sample to just children age 5 or under, who are more likely to stay at home during the day.

One way to reconcile the impacts on self-reported symptoms directly related to pollution with the lack of impact on more objective outcomes is that the self-reports are driven by the "peak-end" effect. A classic psychology finding is that when evaluating experiences, individuals attend primarily to the peak intensity of the experience and the end of the experience (Fredrickson and Kahneman, 1993; Kahneman et al., 1993; Redelmeier and Kahneman, 1996). In our context, this means that when asking someone about their symptoms, they may pay disproportionate attention to the symptoms experienced during peak smoke exposure. Because the intensity of the peaks is reduced by the Jikokoa, these salient experiences may be reduced even without an effect on more enduring measures of health. It is important to note that this does not mean the self reports contain no signal of health experiences, but that they may be driven by peak experiences which may not translate into non-transitory health impacts.

4.4 Heterogeneity of health impacts

We do not find evidence of heterogeneity in treatment impacts along the lines of baseline health, baseline beliefs about future health impacts, age, WTP, baseline charcoal expenditures, or endline LPG ownership (Table A18). Ambient pollution is a potentially important source of heterogeneity, as some previous research has found air pollution improvements to be non-linear—either concave or convex—in average pollution. We test for heterogeneity in the primary treatment effect on health by whether the respondent has above or below median ambient air pollution. To avoid bias due to adoption endogeneity and noise in the time use data, we define a respondent's ambient pollution as average pollution among the five respondents residing nearest that respondent. We then test whether the health impacts differ by whether respondents' ambient exposure is above vs the median. We find no difference of heterogeneity along this dimension, at least over the range of pollution levels we observe (Table A19).

Since ambient pollution levels are generally lower in rural areas than in urban areas, study participants residing in rural areas may experience larger proportional pollution improvements. To examine whether health impacts are different for study participants residing in rural areas, we estimate the causal impact of adoption on health outcomes just among this sample. We do not find evidence of health improvements among this sub-sample—in fact, most point estimates point in the opposite (Table A20). We refrain from over-interpreting this result because the rural sample is very small ($n = 53$) and because moving to a rural area is an endogenous choice that may significantly bias the estimation.

4.5 Impacts of stove ownership on socio-economic outcomes

Panel (B) of Table 3 presents the impact of stove adoption on various socioeconomic outcomes (Table A3 presents a more detailed version). Among the urban sample, improved cookstove ownership causes a \$1.65 reduction in weekly charcoal expenditures, about a 44 percent reduction relative to the control group (Table A3). This adds up to approximately \$86 per year—a statistically and economically significant result, though the estimate is slightly lower than short- and medium-term impacts (Berkouwer and Dean, 2022a). Rural residents spend less than half as much on charcoal per week as urban residents.[30] The combined treatment effect for the full sample is therefore slightly lower; \$1.50 per week on average. These results demonstrate that the stoves have both large private and social benefits.

In addition, Jikokoa adoption increases the propensity of individuals in an adopter's network to adopt the stove. Specifically, it roughly doubles the number of Jikokoa stoves owned by members in a respondent's network such as friends, family, and in particular neighbors (Table A3). We see no impacts on earnings, savings, or formal banking access, suggesting the financial savings may have been spent on consumption. In terms of other behavioral outcomes, we see no impacts on time spent on various activities such as sleeping, working, eating, or walking (Table A4).

4.6 Robustness tests and attrition

A critical concern when using self-reported data is whether self-reports are driven by experimenter demand. Participants who received a (sometimes very heavily) subsidized cookstove might be more inclined to report better health than those who did not. While we cannot rule out some amount of experimenter demand, several factors weigh against this fully explaining the effects. First, we test whether those with higher subsidies are more likely to report positive health even after controlling for stove adoption. If respondents with a lower price (higher subsidy) were more likely to self-report better health, price would correlate directly with self-reported symptoms rather than purely through the adoption channel ('owns Jikokoa'). We do not find evidence of this (Table A21). Second, self-reported health improvements arise primarily through respiratory rather than non-respiratory symptoms: participants would thus have to be sophisticated about which types of health symptoms they report improvements in. Third, the relationship between health and pollution is similar in magnitude when constraining the sample to non-adopters only (Table A26).

[30] Households living in rural areas are more likely to use firewood, gathered at little cost.

702 of the 942 respondents (75%) were surveyed successfully during the three-year follow-up survey. Attrition is not correlated with their randomly assigned BDM price, credit treatment assignment, initial Jikokoa stove adoption, or baseline health outcomes (Table A23). 53 of the respondents who did not complete the three-year follow-up survey had moved outside to locations the three study areas—either elsewhere in Nairobi or elsewhere in Kenya—but where our survey team could still reach them. 65% of those who were not surveyed could not be contacted; the remainder were not surveyed because they said they were unavailable, withdrew from the study, or relocated to locations outside of the survey team's reach (Table A22). Attrition is slightly higher among respondents with fewer children, fewer household members, and younger respondents (such respondents may more easily move around, making them harder to track).

5 The relationship between pollution and health

There is uncertainty in the literature about which moments of the pollution exposure matter for health. Unfortunately, using an instrumental variables approach to estimate the impacts of these different moments causally lacks precision (the Cragg-Donald Wald F-statistic on a weak identification test is 1.4) and also potentially violates the exclusion restriction as there are multiple channels through which stove adoption could affect health outcomes.

Instead, we provide some evidence by using standard OLS regressions to estimate the correlation between health and three key moments of pollution: average pollution exposure (in 100 $\mu g/m^3$), peak pollution exposure (defined as the highest hourly average recorded, in 100 $\mu g/m^3$), and the duration of high pollution exposure (defined as the number of hours pollution was above in 100 $\mu g/m^3$). Table 7 presents the results. Table A25 provides a version with additional detail, and also provides specifications that control for average pollution to look at the effect of peakiness as distinct from higher average pollution.

Mean and median PM2.5 air pollution are not correlated with self-reported health symptoms, while maximum hourly pollution is. Peaks in air pollution exposure may have very different health impacts than the mean daily levels that were investigated in much of the literature studying ambient air pollution (Chay and Greenstone (2003), Clay, Lewis, and Severnini (2022), Currie and Walker (2011), Deryugina et al. (2019), Ebenstein et al. (2017), Greenstone and Hanna (2014), Isen, Rossin-Slater, and Walker (2017), and Schlenker and Walker (2015)).

6 Conclusion

Air pollution is a significant contributor to global morbidity and mortality. Most air pollution falls broadly into one of two categories: peak pollution exposures—primarily generated by a household's private actions, such as cooking—and ambient pollution—primarily generated by other actors, such as factories, industry, power plants, or even neighbors' cookstove usage. Billions of the world's urban poor face both types of air pollution on a daily basis, yet there is little evidence on which policy

Table 7: Correlations with mean, median, maximum, and duration of PM2.5 exposure

	Mean	Mean Pollution in SD	Median Pollution in SD	Max Hourly Pollution in SD	Hours Above $100\mu g/m^3$	N
	(1)	(2)	(3)	(4)	(5)	(6)
Hypertension (>130/80)	0.51	0.01	-0.02	0.00	0.00	645
	[0.50]	(0.02)	(0.02)	(0.02)	(0.01)	
Blood oxygen	96.72	0.12	0.12	-0.03	0.03	645
	[2.43]	(0.10)	(0.11)	(0.10)	(0.06)	
Health symptoms z-score	-0.09	0.01	-0.01	0.07**	0.01	651
	[0.92]	(0.04)	(0.04)	(0.04)	(0.02)	
Number of health symptoms	2.52	0.02	-0.00	0.23**	0.02	651
	[2.66]	(0.11)	(0.11)	(0.10)	(0.06)	
Health diagnoses index	-0.04	-0.04	-0.05	0.00	-0.03	651
	[0.89]	(0.04)	(0.04)	(0.04)	(0.02)	
Number of health diagnoses	0.29	-0.03	-0.02	-0.00	-0.02	651
	[0.56]	(0.02)	(0.03)	(0.02)	(0.01)	
Hospital visits in past 30 days	0.30	-0.01	-0.01	0.01	-0.00	651
	[0.55]	(0.02)	(0.02)	(0.02)	(0.01)	
Hospital expenditures (USD)	2.82	0.66	0.40	0.62	0.26	651
	[10.14]	(0.44)	(0.45)	(0.42)	(0.24)	

Each row and column cell in columns (2)–(5) is a separate OLS regression. All regressions include socioeconomic controls, air pollution device FE, month of survey, and baseline WTP. Hypertension refers to stage 1. Table A25 shows additional variables. Table A12, Table A13, and Table A14 present detailed results on symptoms and diagnoses.

makers seeking to improve health should prioritize. To fill this gap, we investigate the impacts of reducing peak pollution exposures in the presence of high ambient air pollution, using a randomized experiment studying an improved biomass cookstove in Kenya. Randomized subsidies and access to credit yield a persistent increase in adoption of a more energy efficient biomass cookstove. This allows us to asses the health impacts of owning an improved stove for three and a half years. We find that improved stove ownership causes a large reduction in peak air pollution generated during cooking hours. As a result, households experience a 0.24 standard deviation improvement in self-reported respiratory symptoms.

However, since we observe no reduction during the remaining 22 hours of the day, and given the high levels of ambient pollution in this urban context, we see only a very small and statistically insignificant effect on average air pollution exposure. This can explain the comprehensive lack of impacts on a host of quantitative health measurements (including blood pressure and blood oxygen) and self-reported diagnoses of chronic diseases such as pneumonia, as well as several key health outcomes for children. These results suggest that the urban poor have only limited ability to improve their health through the private adoption of improved technologies in contexts with high ambient air pollution.

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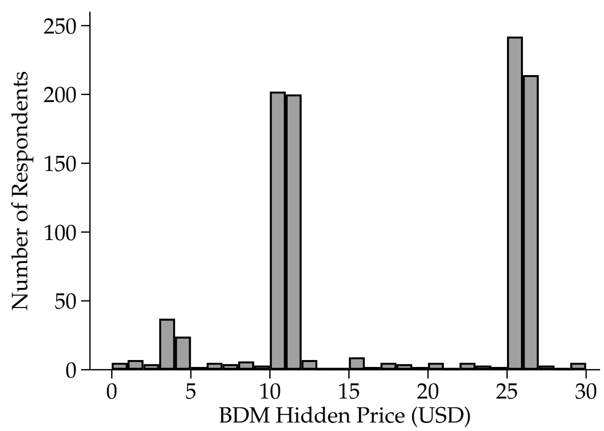
Figure A1: Traditional *jiko* ('stove') and energy efficient stove

Reproduced from Berkouwer and Dean (2022a). On the left is the traditional *jiko*. On the right is the energy efficient stove. The two stoves use the same type of charcoal and the same process for cooking food, hence the energy efficient stove requires essentially no learning to adopt. After usage, the user disposes of the ash using the tray at the bottom. The central chamber of the energy efficient stove is constructed using insulating materials.

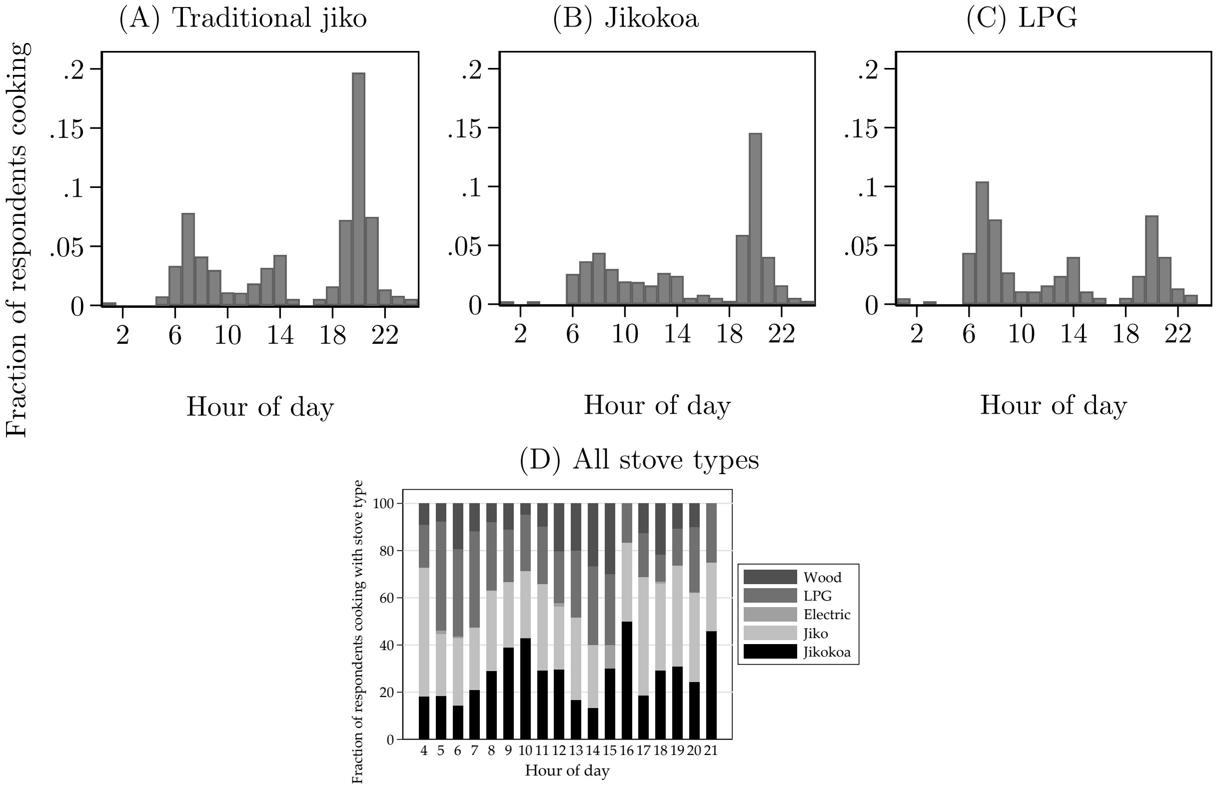
A Online Appendix Figures

Figure A2: BDM Hidden price distribution



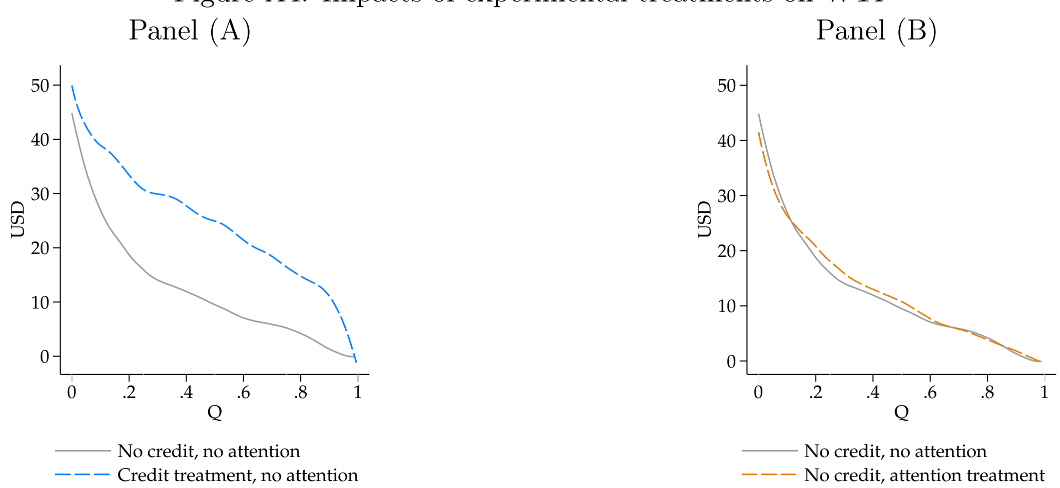
Reproduced from Berkouwer and Dean (2022a). The distribution of prices P_i used in the BDM elicitation mechanism. 6 percent of participants are allocated a price drawn from $U[3.50, 4.50]$, 39 percent of participants are allocated a price drawn from $U[10, 12]$, and 44 percent of participants are allocated a price drawn from $U[25, 27]$. The remaining prices are drawn from a uniform distribution over the entire interval $U[0.01, 29.99]$. Respondents buy the stove if and only if $WTP_i \geq P_i$.

Figure A3: Time use data: cooking hours by cooking technology



Panels (A), (B), and (C) show the fraction of respondents who report using a particular cooking technology across the various hours of the day. Panel (D) shows the same as a fraction of people who report cooking during that hour.

Figure A4: Impacts of experimental treatments on WTP



Note: This figure has been reproduced in its entirety from Berkouwer and Dean (2022a). Graphs show the cumulative distribution of WTP for the control and treatment groups for both treatments. Panel A presents results by credit treatment status among people in the attention control group only. Panel B presents results by attention treatment status among people in the credit control group only. Access to credit increases WTP by USD 13 (104 percent relative to control). Attention to benefits does not affect WTP.

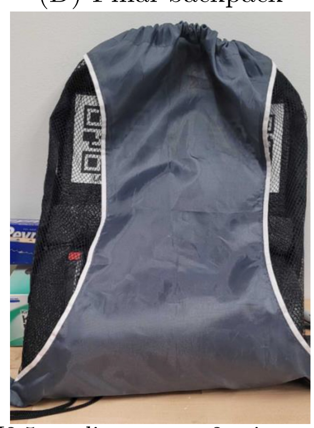
Figure A5: Devices to record air pollution and mesh backpacks containing them

(A) Particulate Matter

(B) Carbon Monoxide

(C) Backpack contents

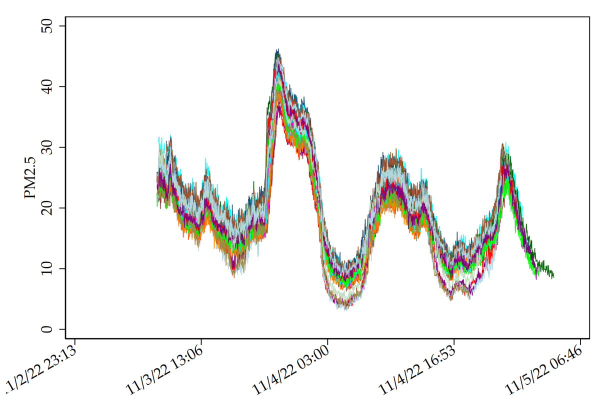
(D) Final backpack



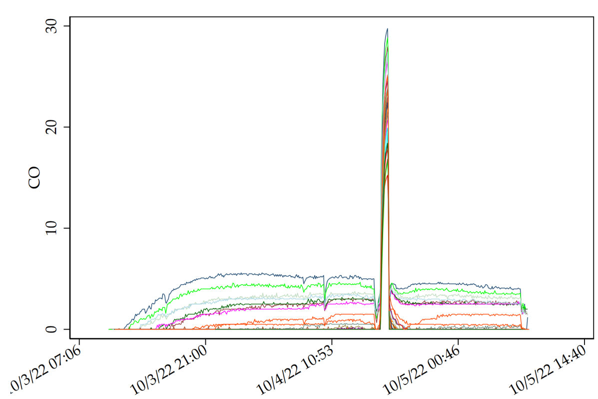
Panel A shows a Purple Air Inc. device, which records PM1.0 and PM2.5 readings every 2 minutes. Panel B shows a Lascar Electronics device, which records one CO reading every minute. Panel C displays how the devices are affixed to a lightweight foam material to stay in place. Behind the purple air device is a battery. Panel D displays the final backpack as deployed with respondents.

Figure A6: Co-located air pollution readings for devices

A) PM2.5 (PA-II devices)

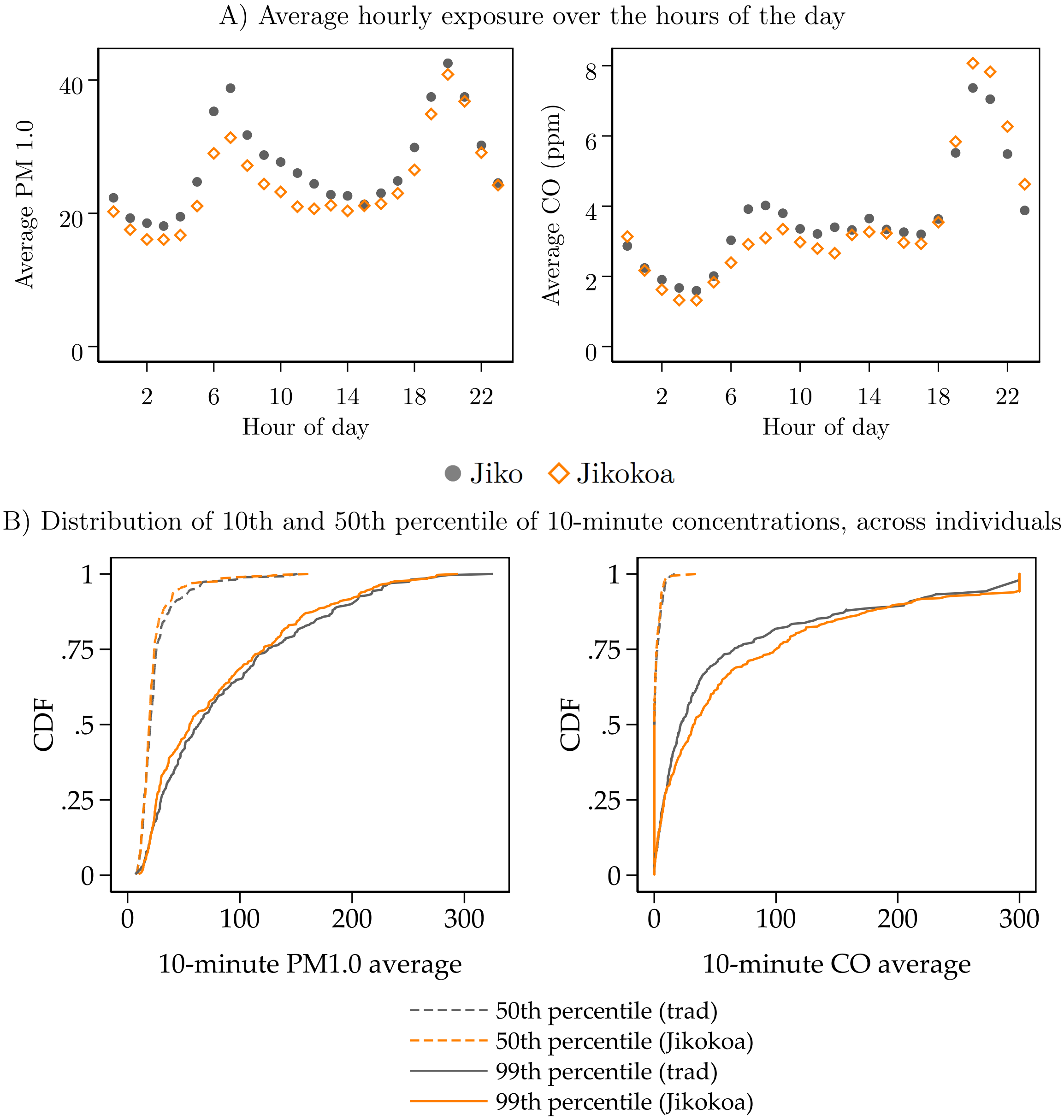


B) CO (LASCAR devices)



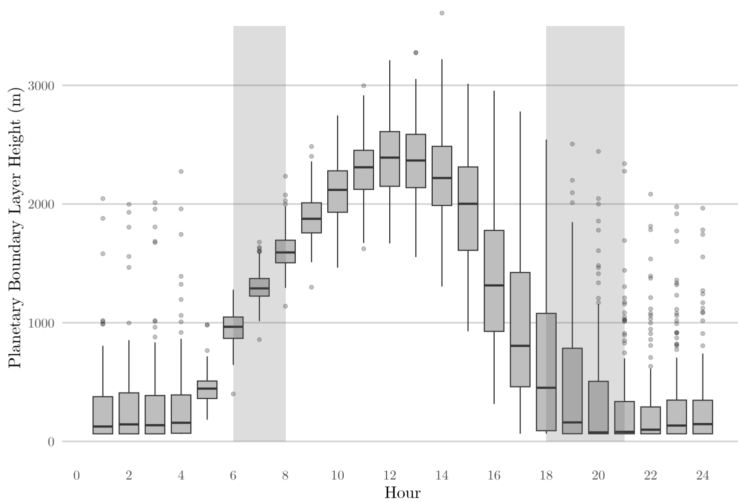
Air pollution data from a 48-hour testing window during which all 68 devices (34 PA-II devices and 34 LASCAR devices) were placed in the same location (Busara offices). To capture level differences across devices, all regressions include device fixed effects where relevant.

Figure A7: Particulate Matter (PM1.0, in $\mu g/m^3$) and Carbon Monoxide pollution by Jikokoa ownership



Panel A presents average PM1.0 and CO exposure by hour of day and endline Jikokoa ownership, as collected by respondents wearing backpacks for on average 48 hours. Panel B presents the distribution of mean and 99th percentile 10-minute average exposure across respondents. Figure 3 presents the same for PM2.5.

Figure A8: Planetary boundary layer height using MERRA-2 satellite data



The figure shows an hourly box plot of the Planetary Boundary layer Height as reported in the NASA MERRA-2 satellite data from the study period. Typical breakfast and dinner hours are shaded in gray. The figure shows that the median height during breakfast is more than one and a half kilometers higher than the median height during dinner.

B Online Appendix Tables

Table A1: Pollution during self-reported time use activities

Activity	Hours	PM2.5	CO
Cooking	2.6	46.0	8.7
	[1.7]	[34.4]	[13.4]
Sleeping	8.1	31.2	4.3
	[2.4]	[20.1]	[7.0]
Eating	2.5	42.6	8.5
	[1.1]	[33.3]	[13.0]
Bus	0.4	32.9	6.7
	[1.1]	[19.3]	[12.8]
Bicycle	0.0	45.1	5.1
	[0.2]	[56.3]	[7.4]
Walking	1.9	35.0	5.6
	[2.3]	[28.3]	[11.2]
Work	5.2	37.6	5.7
	[4.7]	[28.0]	[8.9]
Schoolwork	0.1	40.8	9.4
	[0.3]	[32.3]	[17.0]
Other (away)	0.9	37.1	6.9
	[1.6]	[32.1]	[16.5]
Other (home)	4.0	37.5	7.7
	[3.5]	[24.5]	[10.8]

Average hourly air pollution matched with hourly self-reported time use data. Hours add up to >24 if respondents report multiple activities in one hour. PM2.5 in ug/m^3. CO in ppm. Walking refers to walking outdoors, within or across neighborhoods.

Table A2: First stage: impact of random treatments on take-up

	(1)	(2)	(3)	(4)	(5)
Credit treatment	0.29***		0.30***	0.21***	0.20**
	(0.04)		(0.04)	(0.08)	(0.08)
Subsidy (10 USD)		0.20***	0.20***	0.23***	0.23***
		(0.02)	(0.02)	(0.03)	(0.04)
Credit treatment X Subsidy (10 USD)				0.00	0.00
				(0.00)	(0.00)
Socioeconomic controls	No	No	No	No	Yes
Observations	702	702	702	702	702
Control mean	0.4	0.4	0.2	0.2	0.2

Impact of randomly assigned subsidy (between USD 0-40), credit treatment status, and their interaction on Jikokoa ownership, estimated using ordinary least squares regressions (OLS). Column (1) presents the OLS estimate of the effect of the credit treatment on take-up of the Jikokoa. Column (2) presents the OLS estimate of the effect the randomly assigned subsidy (normalized to 10 USD) on Jikokoa take-up. Column (3) presents the OLS estimate of both the credit treatment and randomly assigned subsidy on Jikokoa take-up. Columns (4) and (5) presents the OLS estimate of the credit treatment, randomly assigned subsidy, and their interaction on Jikokoa take-up. Column (5) includes socioeconomic controls.

Table A3: More detailed socio-economic outcomes

	Control Mean	Treatment Effect	N
Charcoal expenditures past 7 days (USD)	3.84	-1.50***	702
	[3.16]	(0.47)	
Charcoal expenditures past 7 days (log)	5.98	-0.33***	667
	[0.82]	(0.12)	
Earnings past 2 weeks (USD)	32.53	4.73	563
	[35.41]	(7.83)	
Has formal bank account (=1)	0.13	0.11	702
	[0.34]	(0.07)	
Total savings (USD)	53.64	-8.63	701
	[86.62]	(19.88)	
... in mobile banking (USD)	5.85	-0.22	702
	[12.29]	(2.05)	
... contributions to SACCO (USD)	7.93	-0.67	701
	[14.30]	(2.69)	
... in SACCO payout (USD)	40.25	-15.30	701
	[64.75]	(13.97)	
... in formal banking (USD)	7.63	6.81	702
	[34.99]	(8.69)	
Minutes cooking per day	136.72	3.49	702
	[57.76]	(8.32)	
... minutes in the morning	30.97	-0.20	702
	[18.73]	(2.81)	
... minutes in the afternoon	40.53	1.17	702
	[25.05]	(4.06)	
... minutes in the evening	65.22	2.53	702
	[31.56]	(4.19)	
People in network who adopted Jikokoa	0.78	1.13***	702
	[2.04]	(0.40)	
... neighbors	0.28	0.56***	702
	[0.82]	(0.16)	
... family members	0.20	0.21	702
	[0.69]	(0.13)	
... friends	0.20	0.22*	702
	[0.69]	(0.13)	
... other people	0.10	0.14	702
	[0.45]	(0.10)	

Each row is an instrumental variables regressions where the randomly assigned price, credit treatment status, and their interaction are used as instruments for endline Jikokoa ownership, and includes socioeconomic controls. The lower number of observations (<702) for "Charcoal expenditures past 7 days (log)" can be attributed to participants reporting zero charcoal expenditures in the past seven days. The lower number of observations for the other rows can be attributed to participants declining to answer.

Table A4: Impacts on Time Use

	Control Mean	Treatment Effect	N
Cooking	2.50	0.31	691
	[1.84]	(0.23)	
Sleeping	9.60	-0.72**	691
	[2.26]	(0.34)	
Eating	2.38	-0.15	691
	[1.07]	(0.17)	
Bus	0.32	-0.05	691
	[0.91]	(0.15)	
Bicycle	0.03	0.01	691
	[0.17]	(0.04)	
Walking	1.67	0.37	691
	[2.01]	(0.33)	
Work	4.40	0.35	691
	[4.12]	(0.67)	
Schoolwork	0.08	0.03	691
	[0.34]	(0.04)	
Other (away)	0.82	-0.29	691
	[1.54]	(0.26)	
Other (home)	3.86	-0.13	691
	[3.21]	(0.51)	

Each row is an instrumental variables regression where the randomly assigned price, credit treatment status, and their interaction are used as instruments for endline Jikokoa ownership. Each regression includes socioeconomic controls. The outcome variable for each row is hours spent on each task each day. Rows add up to > 24 as some respondents report multiple activities within a given hour window.

Table A5: Correlation of Time Use and Pollution Exposure

	Mean	PM2.5	CO
	(1)	(2)	(3)
Jikokoa: Indoors (=1)	0.54	0.16	0.82**
	[1.06]	(0.82)	(0.32)
Jikokoa: Outdoors (=1)	0.08	-3.02	-0.29
	[0.38]	(2.10)	(0.81)
Jiko: Indoors (=1)	0.64	1.09	0.43
	[1.31]	(0.68)	(0.26)
Jiko: Outdoors (=1)	0.18	1.13	0.18
	[0.96]	(0.89)	(0.34)
LPG: Indoors (=1)	0.59	-1.12	-0.46
	[0.99]	(0.89)	(0.35)
LPG: Outdoors (=1)	0.00	-2.96	-0.03
	[0.04]	(18.90)	(7.31)
Wood Fire: Indoors (=1)	0.09	0.77	-1.10*
	[0.51]	(1.59)	(0.62)
Wood Fire: Outdoors (=1)	0.04	5.05***	0.62
	[0.49]	(1.70)	(0.66)
Electric: Indoors (=1)	0.02	1.50	-1.73
	[0.16]	(4.94)	(1.91)
Other stove: Indoors (=1)	0.27	0.70	0.43
	[0.71]	(1.19)	(0.46)
Sleeping	6.09	-0.05	-0.06
	[2.74]	(0.32)	(0.12)
Eating away from home	1.91	-0.94	-0.51
	[0.93]	(1.00)	(0.39)
Eating at home	0.55	2.04**	0.10
	[0.93]	(0.93)	(0.36)
On Bus	0.38	-1.52**	-0.21
	[1.11]	(0.75)	(0.29)
On Bike	0.03	-0.45	0.72
	[0.19]	(4.18)	(1.62)
Walking	1.93	0.10	-0.04
	[2.32]	(0.38)	(0.15)
At work: Indoors	2.22	0.23	-0.04
	[3.81]	(0.31)	(0.12)
At work: Outdoors	2.96	0.27	0.08
	[4.05]	(0.29)	(0.11)
Doing Schoolwork: Outdoors	0.01	-0.99	-1.03
	[0.20]	(4.42)	(1.71)
Doing Schoolwork: Indoors	0.07	-2.09	-0.17
	[0.34]	(2.67)	(1.03)
Other activities: Away	0.84	0.39	0.11
	[1.63]	(0.54)	(0.21)
Other activities: Home	3.99	0.51	0.30**
	[3.56]	(0.33)	(0.13)
Observations	648	642	642

Column 1 presents the mean hours per day participants were doing the activities in each row. Columns 2 and 3 are separate OLS regressions of either Pm2.5 or CO exposure on the list of activities. No one in our sample used an electric stove or “other" stove outdoors.

Table A6: Causal impact of cookstove adoption on pollution exposure (in logs)

Panel A) All

	PM2.5				CO		
	(1) Median	(2) Mean	(3) Max Hour	(4) 99th	(5) Mean	(6) Max Hour	(7) 99th
Own Jikokoa	-0.01	-0.03	-0.13	-0.07	0.48	0.51*	0.56**
	(0.06)	(0.08)	(0.14)	(0.14)	(0.33)	(0.30)	(0.28)
Control Mean	3.1	3.5	4.8	5.0	0.7	2.8	3.1
Weak IV F-Statistic	53	53	53	53	53	53	53
Observations	651	651	651	651	652	651	645

Panel B) When self-reporting cooking

	PM2.5				CO		
	(1) Median	(2) Mean	(3) Max Hour	(4) 99th	(5) Mean	(6) Max Hour	(7) 99th
Own Jikokoa	-0.17*	-0.25**	-0.29*	-0.37**	0.17	0.18	0.15
	(0.09)	(0.11)	(0.15)	(0.18)	(0.41)	(0.41)	(0.37)
Control Mean	3.4	3.7	4.1	4.6	0.9	1.8	2.5
Weak IV F-Statistic	48	48	48	48	45	44	45
Observations	598	598	595	598	548	546	548

Panel C) Between 6–8am and 6–9pm (when most respondents report cooking)

	PM2.5				CO		
	(1) Median	(2) Mean	(3) Max Hour	(4) 99th	(5) Mean	(6) Max Hour	(7) 99th
Own Jikokoa	-0.09	-0.12	-0.23	-0.16	0.26	0.33	0.24
	(0.08)	(0.10)	(0.14)	(0.15)	(0.37)	(0.35)	(0.31)
Control Mean	3.5	3.8	4.5	5.0	1.0	2.3	2.9
Weak IV F-Statistic	53	53	53	53	50	50	50
Observations	649	649	646	649	628	628	628

Panel D) When self-reporting not cooking

	PM2.5				CO		
	(1) Median	(2) Mean	(3) Max Hour	(4) 99th	(5) Mean	(6) Max Hour	(7) 99th
Own Jikokoa	-0.01	-0.03	-0.11	-0.06	0.55*	0.55*	0.47*
	(0.06)	(0.08)	(0.14)	(0.15)	(0.33)	(0.31)	(0.28)
Control Mean	3.1	3.5	4.7	5.0	0.6	2.7	3.1
Weak IV F-Statistic	53	53	53	53	53	53	52
Observations	651	651	651	651	651	651	643

Instrumental variables regressions where the randomly assigned price, credit treatment status, and their interaction are used as instruments for endline Jikokoa ownership. We omit presenting median CO in log because 55% of 10-minute average observations equal 0. Columns (1) and (5) use median exposure, (2) and (6) use mean exposure, (3) and (7) use maximum 1-hour average exposure, and (4) and (8) use 99th percentile of 10-min average exposure. Regressions include socioeconomic controls and fixed effects for the specific LASCAR or PA-II device used for that respondent. Table 4 presents the same for all hours and for when self-reporting cooking.

Table A7: Causal impact of cookstove adoption on pollution exposure

Panel A) Between 6–8am and 6–9pm (when most respondents report cooking)

	PM2.5				CO			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Median	Mean	Max Hour	99th	Median	Mean	Max Hour	99th
Own Jikokoa	-7.1	-9.4	-28.6*	-23.2	0.5	5.1*	18.4*	21.2
	(4.3)	(5.7)	(16.3)	(22.9)	(1.7)	(3.0)	(10.6)	(15.3)
Control Mean	37.4	53.3	117.0	189.8	3.4	9.3	33.1	54.8
Weak IV F-Statistic	53	53	53	53	52	52	52	52
Observations	649	649	646	649	656	656	656	656

Panel B) When self-reporting not cooking

	PM2.5				CO			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Median	Mean	Max Hour	99th	Median	Mean	Max Hour	99th
Own Jikokoa	-0.0	-0.7	-15.0	-5.8	-0.6	2.0	18.8	23.9*
	(1.7)	(3.3)	(18.2)	(23.1)	(0.4)	(1.6)	(12.3)	(14.2)
Control Mean	24.7	36.2	138.5	189.1	1.8	6.2	46.5	57.7
Weak IV F-Statistic	53	53	53	53	52	52	52	52
Observations	651	651	651	651	656	656	656	656

Instrumental variables regression where the randomly assigned price, credit treatment status, and their interaction are used as instruments for endline Jikokoa ownership. Columns (1) and (5) use median exposure, (2) and (6) use mean exposure, (3) and (7) use maximum 1-hour average exposure, and (4) and (8) use 99th percentile of 10-min average exposure. Regressions include socioeconomic controls and fixed effects for the specific LASCAR or PA-II device used for that respondent. Table 4 presents the same for all hours and for when self-reporting cooking. Table A6 presents all four outcomes in logs.

Table A8: Causal impact of cookstove adoption on pollution exposure using hourly data

	Cooking	PM 2.5		PM 1.0		CO	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	IV	OLS	IV	OLS	IV	OLS	IV
Own Jikokoa	0.00	-1.79	0.41	-1.13	0.15	0.89	2.84**
	(0.01)	(1.54)	(2.91)	(0.91)	(1.74)	(0.69)	(1.44)
Cooking and Own Jikokoa		-9.76***	-15.04**	-5.18***	-8.37**	1.30	-1.45
		(3.05)	(7.30)	(1.78)	(4.21)	(1.37)	(2.43)
Cooking		9.20***	12.10***	5.04***	6.79***	0.78	2.30
		(2.56)	(4.04)	(1.53)	(2.31)	(0.83)	(1.54)
DoW*HoD*Geocluster FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	0.10	36.32	36.32	25.65	25.65	6.17	6.17
Weak IV F-Statistic	39		29		29		29
Households	661	652	652	652	652	656	656
Observations	29428	23380	23380	23380	23380	29154	29154

Columns (2), (4), and (6) are each OLS regressions, while Columns (3), (5), and (7) are instrumental variables regressions which use randomly assigned price and credit treatment status as instruments for endline Jikokoa ownership. Standard errors clustered by respondent. All regressions include socioeconomic controls, panel data fixed effects, and Lascar or PA-II device fixed effects.

Table A9: Causal impact of cookstove adoption on propensity to cook indoors

	(1)
Own Jikokoa	-0.026
	(0.047)
Control Mean	0.889
Weak IV F-Stat	46
Observations	649

Instrumental variables regressions using randomly assigned price and credit treatment status as instruments for endline Jikokoa ownership. Regression includes socioeconomic controls.

Table A10: Causal impact of cookstove adoption on minutes per day in excess of exposure thresholds

Panel A) All

	(1)	(2)	(3)	(4)	(5)	(6)
	$50\mu g/m^3$	$75\mu g/m^3$	$100\mu g/m^3$	$200\mu g/m^3$	$300\mu g/m^3$	$400\mu g/m^3$
Own Jikokoa	1.3	-2.7	-2.8	-2.2	-2.4	-2.1
	(30.8)	(23.3)	(18.6)	(10.7)	(7.3)	(4.9)
Households	653	653	653	653	653	653
Control Mean	193.5	120.8	86.3	36.1	20.4	12.6

Panel B) When self-reporting cooking

	(1)	(2)	(3)	(4)	(5)	(6)
	$50\mu g/m^3$	$75\mu g/m^3$	$100\mu g/m^3$	$200\mu g/m^3$	$300\mu g/m^3$	$400\mu g/m^3$
Own Jikokoa	-4.7	-5.5	-4.3	-3.9	-4.4**	-2.6*
	(8.0)	(6.2)	(5.0)	(3.0)	(2.1)	(1.5)
Households	599	599	599	599	599	599
Control Mean	35.6	24.2	17.7	8.5	5.3	3.3

Each column is an instrumental variables regression where the randomly assigned price, credit treatment status, and their interaction are used as instruments for endline Jikokoa ownership. Column labels are the exposure thresholds. Regressions include socioeconomic controls and fixed effects for the specific LASCAR or PA-II device used for that respondent.

Table A11: Causal impact of cookstove adoption on types of food cooked

	Control Mean	Treatment Effect	N
Ugali	0.97	-0.00	702
	[0.17]	(0.02)	
Vegetables	0.94	0.03	702
	[0.24]	(0.05)	
Potatoes	0.79	0.02	702
	[0.41]	(0.06)	
Fish	0.59	-0.00	702
	[0.49]	(0.07)	
Beans	0.90	0.00	702
	[0.30]	(0.05)	
Githeri	0.86	0.10**	702
	[0.34]	(0.05)	
Meat	0.78	0.02	702
	[0.42]	(0.06)	
Chapati	0.75	0.03	702
	[0.44]	(0.06)	
Egg	0.75	0.00	702
	[0.44]	(0.06)	
Tea	0.96	-0.01	702
	[0.20]	(0.02)	
Other foods	0.21	0.12**	702
	[0.41]	(0.06)	

Each row is an instrumental variables regression where the randomly assigned price, credit treatment status, and their interaction are used as instruments for endline Jikokoa ownership. Regressions include socioeconomic controls. Respondents were not asked to provide information about what "other foods" they cooked.

Table A12: Respiratory-related health symptoms

	Control Mean	Treatment Effect	N
Respiratory health symptom index	-0.00	-0.24*	702
	[1.00]	(0.13)	
Number of respiratory health symptoms	1.70	-0.48**	702
	[1.76]	(0.23)	
Respiratory health symptom index (frequent symptoms)	0.00	-0.32**	702
	[1.22]	(0.16)	
Number of respiratory health symptoms (frequent symptoms)	1.61	-0.46**	702
	[1.63]	(0.22)	
Persistent cough	0.24	-0.09	702
	[0.43]	(0.07)	
Always feeling tired	0.30	-0.07	702
	[0.46]	(0.07)	
Breathlessness at night	0.08	-0.01	702
	[0.27]	(0.04)	
Frequent diarrhea	0.02	-0.02	702
	[0.15]	(0.03)	
Difficulty breathing / Chest tightness	0.07	-0.01	702
	[0.26]	(0.04)	
Runny nose	0.23	-0.05	702
	[0.42]	(0.07)	
Sore throat	0.16	-0.12*	702
	[0.37]	(0.06)	
Headache	0.52	-0.12	702
	[0.50]	(0.08)	
Wheezing	0.03	0.01	702
	[0.17]	(0.03)	
Persistent mucus problems	0.04	-0.01	702
	[0.19]	(0.02)	

Each row is an instrumental variables regression where the randomly assigned price, credit treatment status, and their interaction are used as instruments for endline Jikokoa ownership. Regressions include socioeconomic controls. Rows 3 and 4 only include symptoms with prevalence of at least 5% among the control group.

Table A13: Non-respiratory related health symptoms

	Control Mean	Treatment Effect	N
Non-respiratory health symptom index	-0.00	-0.03	702
	[1.00]	(0.19)	
Number of non-respiratory health symptoms	1.09	-0.24	702
	[1.54]	(0.25)	
Non-respiratory health symptom index (frequent symptoms)	-0.00	-0.38*	702
	[1.22]	(0.20)	
Number of non-respiratory health symptoms (frequent symptoms)	0.84	-0.33*	702
	[1.16]	(0.19)	
Fever	0.20	0.01	702
	[0.40]	(0.07)	
Malaria	0.15	-0.13*	702
	[0.36]	(0.07)	
Stomach pain	0.16	-0.11*	702
	[0.37]	(0.06)	
Pain when urinating	0.01	-0.01	702
	[0.10]	(0.03)	
Worms	0.01	0.05**	702
	[0.11]	(0.02)	
Rapid weight loss	0.06	-0.09**	702
	[0.24]	(0.04)	
Frequent and excessive urination	0.03	0.02	702
	[0.16]	(0.02)	
Skin Rash or irritaion	0.02	0.04	702
	[0.12]	(0.03)	
Constant thirst / increased drinking of fluids	0.14	-0.01	702
	[0.35]	(0.05)	
Difficulty swallowing	0.03	-0.02	702
	[0.17]	(0.02)	
Muscle pain (myalgia)	0.12	-0.01	702
	[0.32]	(0.05)	
Loss of sense of smell / not being able to taste food	0.05	-0.01	702
	[0.21]	(0.03)	
Diarrhea / Nausea / Vomiting	0.05	-0.04	702
	[0.21]	(0.03)	
Swelling in ankles, feets or legs	0.04	0.00	702
	[0.20]	(0.03)	
Other accidents	0.02	0.07***	702
	[0.14]	(0.02)	

Each row is an instrumental variables regression where the randomly assigned price, credit treatment status, and their interaction are used as instruments for endline Jikokoa ownership. Regressions include socioeconomic controls. Rows 3 and 4 only include symptoms with prevalence of at least 5% among the control group.

Table A14: Diagnoses by a doctor

	Control Mean	Treatment Effect	N
Number of health diagnoses	0.30	0.13	702
	[0.58]	(0.09)	
Asthma	0.01	-0.01	702
	[0.08]	(0.01)	
Pneumonia	0.13	0.02	702
	[0.34]	(0.05)	
Chronic Pulmonary Disease	0.00	0.01	702
	[0.06]	(0.01)	
Other lung disease	0.01	-0.01	702
	[0.08]	(0.01)	
Stroke or cardiovascular disease	0.01	-0.00	702
	[0.08]	(0.01)	
Hypertension	0.05	0.11***	702
	[0.22]	(0.04)	
Tuberculosis	0.01	0.02	702
	[0.08]	(0.01)	
COVID	0.01	-0.01	702
	[0.08]	(0.01)	
Diabetes	0.02	-0.00	702
	[0.14]	(0.02)	
Other	0.04	0.01	702
	[0.19]	(0.03)	
Typhoid	0.02	0.01	702
	[0.14]	(0.02)	
Tuberculosis	0.01	-0.01	702
	[0.08]	(0.02)	
Cholera	0.00	0.01	702
	[0.00]	(0.01)	

Each variable is the respondent's self-report of whether they have been diagnosed with each disease by a doctor in the past three years. Each row is an instrumental variables regression where the randomly assigned price, credit treatment status, and their interaction are used as instruments for endline Jikokoa ownership. Regressions include socioeconomic controls.

Table A15: Impacts on cognitive function

	Control Mean	Treatment Effect	N
Cognitive index	-0.00	-0.01	587
	[1.00]	(0.15)	
Working memory (Corsi)	-0.00	-0.48**	305
	[1.00]	(0.22)	
Attention (d2)	0.00	-0.09	564
	[1.00]	(0.15)	
Inhibitory control (HF - % correct)	-0.00	0.18	516
	[1.00]	(0.16)	
Inhibitory control (HF - reaction time)	0.00	0.14	516
	[1.00]	(0.19)	

Each row is an instrumental variables regression where the randomly assigned price, credit treatment status, and their interaction are used as instruments for endline Jikokoa ownership. Regressions include socioeconomic controls. See Section 3.4 and Appendix C for descriptions of the cognitive exercises conducted to measure cognitive function. Variables standardized for the control group to have mean 0 and standard deviation 1. Due to a technical issues with the tablets not displaying the behavioral games, the sample size for some of the cognition outcomes is smaller than in other outcome tables. Since this was a technical issue that occurred in the earlier stages of the surveying round, and since the order of follow-up surveys was randomized, it is unlikely that this biased the results in any meaningful way. Regressions control for baseline demographic and socioeconomic characteristics.

Table A16: Healthcare utilization outcomes

	Control Mean (1)	Treatment Effect (2022 Ownership) (2)	Treatment Effect (2019 ownership) (3)	N
Non-hospital health expenditures (USD)	4.34	0.80	0.56	702
	[7.64]	(1.07)	(0.78)	
Hospital visits in past 30 days	0.33	-0.01	-0.01	702
	[0.57]	(0.09)	(0.07)	
Hospital visit expenditures (USD)	3.39	1.03	0.79	702
	[11.17]	(1.48)	(1.08)	

Each row is an instrumental variables regression where the randomly assigned price, credit treatment status, and their interaction are used as instruments for endline Jikokoa ownership. Regressions include socioeconomic controls.

Table A17: Children's outcomes

	Control Mean	Treatment Effect	N
Child weight (kg)	17.73	-1.02	224
	[7.57]	(1.80)	
Child height (cm)	98.59	6.02	199
	[31.07]	(6.08)	
Child arm circumference (cm)	16.37	1.24	220
	[7.26]	(1.41)	
Number of child health symptoms	1.19	0.34	343
	[1.50]	(0.40)	
Child health symptom index	0.00	0.32	343
	[1.00]	(0.29)	
Fever	0.18	-0.01	343
	[0.38]	(0.09)	
Vomiting	0.10	-0.01	343
	[0.30]	(0.06)	
Cough	0.40	0.03	343
	[0.49]	(0.12)	
Diarrhea	0.10	0.00	343
	[0.30]	(0.07)	
Breathlessness	0.04	0.08	343
	[0.19]	(0.06)	
Persistent headache	0.08	0.05	343
	[0.27]	(0.05)	
Very bad cough	0.25	0.10	343
	[0.43]	(0.09)	
Pneumonia - DHS	0.03	0.03	343
	[0.18]	(0.05)	
Pneumonia - WHO	0.16	0.02	343
	[0.21]	(0.06)	

Each row is an instrumental variables regression where the randomly assigned price, credit treatment status, and their interaction are used as instruments for endline Jikokoa ownership. Regressions include household and adult socioeconomic controls. 'Pneumonia - DHS' and 'Pneumonia - WHO' make an attempted pneumonia diagnosis based on self-reported respiratory symptoms and hospital visits using guidelines from the Demographic and Health Survey (DHS) and World Health Organization (WHO), respectively.

Table A18: Heterogeneity in primary health impacts by baseline socioeconomic variables

	Treatment X Age	Treatment X WTP	Treatment X Health	Treatment X Health beliefs	Treatment X LPG	N
	(1)	(2)	(3)	(4)	(5)	
Average systolic blood pressure	-0.73	-2.53	-2.20	-1.51	-0.32	696
	(3.26)	(4.88)	(3.07)	(3.42)	(6.16)	
Average diastolic blood pressure	-2.49	-3.07	-3.77*	-1.58	-0.46	696
	(2.09)	(3.13)	(1.97)	(2.32)	(4.06)	
Hypertension: Stage 1 or higher	-0.01	-0.05	-0.15*	-0.05	-0.06	696
(>130/80)	(0.08)	(0.13)	(0.09)	(0.09)	(0.17)	
Hypertension: Stage 2 or higher	0.03	-0.20*	-0.15*	-0.09	0.04	696
(>140/90)	(0.08)	(0.12)	(0.08)	(0.08)	(0.14)	
Blood oxygen	0.05	0.94	-0.15	-0.05	0.70	696
	(0.33)	(0.60)	(0.35)	(0.37)	(0.67)	
Number of non-respiratory health	0.00	0.31	0.21	0.10	0.44	702
symptoms	(0.20)	(0.35)	(0.21)	(0.29)	(0.48)	
Non-respiratory health symptom index	-0.07	0.10	0.15	0.09	0.32	702
	(0.14)	(0.23)	(0.14)	(0.21)	(0.34)	
Number of respiratory health symptoms	0.25	0.04	-0.12	-0.02	-0.05	702
	(0.20)	(0.34)	(0.21)	(0.24)	(0.45)	
Respiratory health symptom index	0.12	-0.06	-0.07	-0.00	0.12	702
	(0.12)	(0.19)	(0.11)	(0.13)	(0.25)	
Observations						

Each row is an instrumental variables regression where the randomly assigned price, credit treatment status, and their interaction are used as instruments for endline Jikokoa ownership. Regressions include socioeconomic controls. All heterogeneity variables are baseline measures and standardized to have mean 0 and standard deviation 1. There are 48 respondents whos age is >60.

Table A19: Primary health outcomes by ambient concentrations

	Treatment (1)	Treatment X Ambient (2)	N
Average systolic blood pressure	-1.20	3.64	649
	(4.69)	(5.97)	
Average diastolic blood pressure	1.43	-1.06	649
	(2.85)	(4.03)	
Hypertension: Stage 1 or higher (>130/80)	0.07	-0.11	649
	(0.11)	(0.17)	
Hypertension: Stage 2 or higher (>140/90)	-0.02	0.05	649
	(0.10)	(0.15)	
Blood oxygen	-0.08	0.44	649
	(0.41)	(0.67)	
Number of non-respiratory health symptoms	0.12	-0.76	655
	(0.31)	(0.52)	
Non-respiratory health symptom index	0.07	-0.24	655
	(0.22)	(0.38)	
Number of respiratory health symptoms	-0.34	-0.14	655
	(0.28)	(0.45)	
Respiratory health symptom index	-0.17	-0.05	655
	(0.17)	(0.25)	
Health diagnoses index	0.06	0.08	655
	(0.24)	(0.32)	
Number of health diagnoses	0.10	0.06	655
	(0.13)	(0.19)	
Cognitive index	-0.17	0.24	547
	(0.21)	(0.30)	
Non-hospital health expenditures (USD)	1.04	0.25	655
	(1.42)	(2.32)	
Hospital visits in past 30 days	-0.02	0.02	655
	(0.12)	(0.19)	
Hospital visit expenditures (USD)	0.99	2.37	655
	(1.67)	(3.07)	
Observations			

High ambient concentration is a dummy for above median average non-cooking PM2.5. Each row is an instrumental variables regression where the randomly assigned price, credit treatment status, and their interaction are used as instruments for endline Jikokoa ownership. Regressions include socioeconomic controls. Table A12, Table A13, Table A14, and Table A15 present detailed results on the components of the symptoms, diagnoses, and cognitive indices, respectively.

Table A20: Primary health outcomes for rural respondents

	Control Mean (1)	Treatment Effect (2022 Ownership) (2)	Treatment Effect (2019 ownership) (3)	N
Physiology health index (blood oxygen and blood pressure)	-0.03	-1.04***	-0.98***	53
	[0.91]	(0.31)	(0.33)	
Number of non-respiratory health symptoms	0.64	-0.11	-0.11	53
	[0.79]	(0.21)	(0.21)	
Non-respiratory health symptom index	-0.29	0.08	0.07	53
	[0.44]	(0.08)	(0.07)	
Number of respiratory health symptoms	1.23	-0.02	0.06	53
	[1.11]	(0.35)	(0.35)	
Respiratory health symptom index	-0.31	-0.15	-0.13	53
	[0.50]	(0.19)	(0.19)	
Health diagnoses index	-0.16	0.38**	0.41**	53
	[1.18]	(0.18)	(0.19)	
Number of health diagnoses	0.14	0.14	0.14	53
	[0.47]	(0.12)	(0.13)	
Cognitive index	-0.07	0.01	-0.02	51
	[0.80]	(0.28)	(0.28)	
Healthcare utilization index (spending and visits)	0.02	0.80*	0.84*	53
	[0.97]	(0.44)	(0.46)	

Health outcomes for the rural sample only. Each row is an instrumental variables regression where the randomly assigned price, credit treatment status, and their interaction are used as instruments for endline Jikokoa ownership. Regressions include socioeconomic controls. Table A12, Table A13, Table A14, and Table A15 present detailed results on the components of the symptoms, diagnoses, and cognitive indices, respectively. Table 5 presents results for the full sample.

Table A21: Testing for experimenter demand: direct effect of price on symptom reports

	Respiratory			Non-respiratory		
	(1)	(2)	(3)	(4)	(5)	(6)
Owns Jikokoa	-0.45***	-0.29	-0.30	-0.39***	-0.40	-0.38
	(0.12)	(0.28)	(0.28)	(0.11)	(0.26)	(0.27)
Price (10 USD)	-0.00	0.05	0.05	-0.06	-0.07	-0.06
	(0.07)	(0.11)	(0.11)	(0.06)	(0.10)	(0.10)
Owns Jikokoa X Price (10 USD)		-0.09	-0.09		0.00	0.01
		(0.14)	(0.14)		(0.13)	(0.13)
WTP (10 USD)			0.02			-0.02
			(0.05)			(0.05)

Regressions include socioeconomic controls. If respondents with a lower price (higher subsidy) were more likely to self-report better health, price would correlate directly with self-reported symptoms rather than through the adoption channel ('Owns Jikokoa'). We do not find evidence of this here, meaning we do not find evidence of experimenter demand.

Table A22: Attrition: reaching participants

Reason	Frequency
Completed survey	702
Unable to contact	164
Unavailable	13
Withdrew from study	31
Relocated outside survey team reach	29
Deceased	7
Imprisoned	2
Other	7
Total	955

Participants who we were unable to contact were labeled only after repeated phone calls to their phone numbers and to the phone numbers of family members, physical visits to their home locations, and inquiries with nearby participants. Participants were labeled as "relocated outside survey team reach" if they moved out of Kenya or far away from the major cities of Nairobi and Mombasa.

Table A23: Attrition

	Baseline Mean	Attrited	N
BDM Price (USD)	17.6	0.3	955
	[8.3]	(0.6)	
Credit Treatment	0.7	-0.0	955
	[0.5]	(0.0)	
Attention Treatment	0.7	0.1*	955
	[0.5]	(0.0)	
Jikokoa (=1)	0.6	-0.0	955
	[0.5]	(0.0)	
Persistent cough in past week	0.3	-0.0	955
	[0.5]	(0.0)	
Persistent breathlessness in past week	0.3	-0.0	955
	[0.5]	(0.0)	
Hours work missed due to health in past week	3.2	1.1	951
	[14.8]	(1.1)	
Female	1.0	-0.0	955
	[0.2]	(0.0)	
Respondent age	37.5	-3.8***	955
	[11.8]	(0.9)	
Number of household residents	4.8	-0.4**	955
	[2.1]	(0.2)	
Number of child residents	2.6	-0.3*	955
	[1.7]	(0.1)	
Savings in bank, mobile, ROSCA (USD)	75.7	11.8	955
	[130.2]	(9.5)	
Household income (USD/week)	47.3	2.5	949
	[34.8]	(2.6)	
Total energy consumption (USD/week)	8.6	-0.4	955
	[3.6]	(0.3)	
Charcoal consumption (USD/week)	5.6	-0.4*	955
	[2.6]	(0.2)	
Price of old jiko (USD)	3.4	0.2	950
	[1.3]	(0.1)	
Risky investment amount (0-4 USD)	1.2	-0.0	955
	[1.0]	(0.1)	
Mean		0.26	

All variables from baseline (2019). Attrited = 1 if respondent has not completed a 2022–2023 endline survey. Column (1), Baseline Mean, is the mean of both attriters and non-attriters in 2019. Column (2), Attrited, is the difference in means between the full sample and attriters. Any changes in Column (3), N, is due to participants declining to answer a question. The bottom row, Mean, presents the percentage of respondents who attrited.

Table A24: Correlation between health and average, maximum, and duration of PM2.5 exposure

	Mean	Average Pollution in SD	Max Hourly Pollution in SD		Hours Above $100\mu g/m^3$		N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Average systolic blood pressure	123.49	-0.08	0.52	0.52	0.25	0.25	645
	[21.60]	(0.91)	(0.85)	(0.85)	(0.50)	(0.50)	
Average diastolic blood pressure	81.74	0.53	0.53	0.53	0.29	0.29	645
	[12.71]	(0.56)	(0.53)	(0.53)	(0.31)	(0.31)	
Hypertension (>130/80)	0.51	0.01	0.00	0.00	0.00	0.00	645
	[0.50]	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	
Hypertension: Stage 2 or higher	0.27	0.00	-0.01	-0.01	0.00	0.00	645
(>140/90)	[0.44]	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	
Blood oxygen	96.72	0.12	-0.03	-0.03	0.03	0.03	645
	[2.43]	(0.10)	(0.10)	(0.10)	(0.06)	(0.06)	
Number of health symptoms	2.52	0.02	0.23**	0.23**	0.02	0.02	651
	[2.66]	(0.11)	(0.10)	(0.10)	(0.06)	(0.06)	
Health symptoms index (z-score)	-0.09	0.01	0.07**	0.07**	0.01	0.01	651
	[0.92]	(0.04)	(0.04)	(0.04)	(0.02)	(0.02)	
Number of non-respiratory health	0.96	0.03	0.15***	0.15***	0.02	0.02	651
symptoms	[1.44]	(0.06)	(0.06)	(0.06)	(0.03)	(0.03)	
Non-respiratory health symptom	-0.07	0.02	0.09**	0.09**	0.01	0.01	651
index	[0.99]	(0.04)	(0.04)	(0.04)	(0.02)	(0.02)	
Number of respiratory health	1.55	-0.01	0.08	0.08	0.00	0.00	651
symptoms	[1.60]	(0.06)	(0.06)	(0.06)	(0.03)	(0.03)	
Respiratory health symptom index	-0.09	-0.01	0.04	0.04	-0.00	-0.00	651
	[0.88]	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)	
Number of health diagnoses	0.29	-0.03	-0.00	-0.00	-0.02	-0.02	651
	[0.56]	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	
Health diagnoses index	-0.04	-0.04	0.00	0.00	-0.03	-0.03	651
	[0.89]	(0.04)	(0.04)	(0.04)	(0.02)	(0.02)	
Hospital visits in past 30	0.30	-0.01	0.01	0.01	-0.00	-0.00	651
days	[0.55]	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	
Non-hospital health expenditures	4.17	0.63*	0.60*	0.60*	0.28	0.28	651
(USD)	[7.94]	(0.33)	(0.32)	(0.32)	(0.18)	(0.18)	
Hospital visit expenditures (USD)	2.82	0.66	0.62	0.62	0.26	0.26	651
	[10.14]	(0.44)	(0.42)	(0.42)	(0.24)	(0.24)	
Control for average pollution			No	Yes	No	Yes	

Each row and column cell in columns (2)–(6) is a separate OLS regression. Regressions include socioeconomic controls and fixed effects for month surveyed and for the specific LASCAR or PA-II device used for that respondent. Regressions in columns (4) and (6) control for average PM2.5 pollution, while regressions in columns (3) and (5) don't. Table A12, Table A13 and Table A14 present detailed results on symptoms and diagnoses.

Table A25: Correlation between health and average, maximum, and duration of ambient PM2.5 exposure

	Mean	Mean Pollution in SD	Median Pollution in SD	Max Hourly Pollution in SD	Hours Above $100\mu g/m^3$	N
	(1)	(2)	(3)	(4)	(5)	(6)
Hypertension (>130/80)	0.51	0.00	-0.02	0.02	0.00	645
	[0.50]	(0.02)	(0.02)	(0.02)	(0.01)	
Blood oxygen	96.72	0.12	0.11	-0.00	0.03	645
	[2.44]	(0.11)	(0.11)	(0.10)	(0.06)	
Health symptoms index (z-score)	-0.09	0.01	-0.00	0.06*	0.00	651
	[0.92]	(0.04)	(0.04)	(0.04)	(0.02)	
Number of health symptoms	2.51	0.02	0.02	0.17	0.00	651
	[2.68]	(0.11)	(0.11)	(0.10)	(0.06)	
Health diagnoses index	-0.04	-0.04	-0.04	-0.01	-0.03	651
	[0.89]	(0.04)	(0.04)	(0.04)	(0.02)	
Number of health diagnoses	0.29	-0.03	-0.01	-0.02	-0.02	651
	[0.56]	(0.02)	(0.02)	(0.02)	(0.01)	
Hospital visits in past 30 days	0.30	-0.00	0.01	0.00	0.00	651
	[0.55]	(0.02)	(0.02)	(0.02)	(0.01)	
Hospital visit expenditures (USD)	2.82	0.67	0.52	0.73*	0.26	651
	[10.14]	(0.43)	(0.43)	(0.41)	(0.24)	

Each row and column cell in columns (2)–(6) is a separate OLS regression. Regressions include socioeconomic controls and fixed effects for month surveyed and for the specific LASCAR or PA-II device used for that respondent. We define ambient air pollution as the pollution exposure while people report not cooking. Regressions in columns (4) and (6) control for average ambient PM2.5 pollution, while regressions in columns (3) and (5) don't. Column 1 presents the means of the variable in the given row. Table A12, Table A13 and Table A14 present detailed results on symptoms and diagnoses.

Table A26: Correlation between health and mean, median, maximum, and duration of PM2.5 exposure (among non-adopters)

	Mean	Mean Pollution in SD	Median Pollution in SD	Max Hourly Pollution in SD	Hours Above $100\mu g/m^3$	N
	(1)	(2)	(3)	(4)	(5)	(6)
Hypertension (>130/80)	0.52	-0.01	-0.02	-0.01	-0.00	290
	[0.50]	(0.04)	(0.04)	(0.04)	(0.02)	
Blood oxygen	96.58	0.31*	0.27	0.33*	0.14	290
	[2.59]	(0.18)	(0.19)	(0.18)	(0.10)	
Health symptoms index (z-score)	0.02	-0.00	0.03	0.09	-0.00	291
	[1.02]	(0.06)	(0.07)	(0.07)	(0.04)	
Number of health symptoms	2.82	0.01	0.10	0.33*	0.01	291
	[2.96]	(0.18)	(0.19)	(0.19)	(0.10)	
Health diagnoses index	0.01	-0.04	-0.06	0.04	-0.01	291
	[1.00]	(0.07)	(0.07)	(0.07)	(0.04)	
Number of health diagnoses	0.31	-0.01	-0.02	0.04	-0.00	291
	[0.59]	(0.04)	(0.04)	(0.04)	(0.02)	
Hospital visits in past 30 days	0.35	0.02	-0.02	0.05	-0.01	291
	[0.59]	(0.04)	(0.04)	(0.04)	(0.02)	
Hospital visit expenditures (USD)	3.41	1.17	0.58	1.57**	0.29	291
	[10.94]	(0.73)	(0.75)	(0.75)	(0.40)	

Each row and column cell in columns (2)–(5) is a separate OLS regression. Regressions include socioeconomic controls and fixed effects for month surveyed and for the specific LASCAR or PA-II device used for that respondent. Hypertension refers to stage 1. Table 7 present the same for the entire sample.

C Cognitive assessments

C.1 Reverse Corsi Block

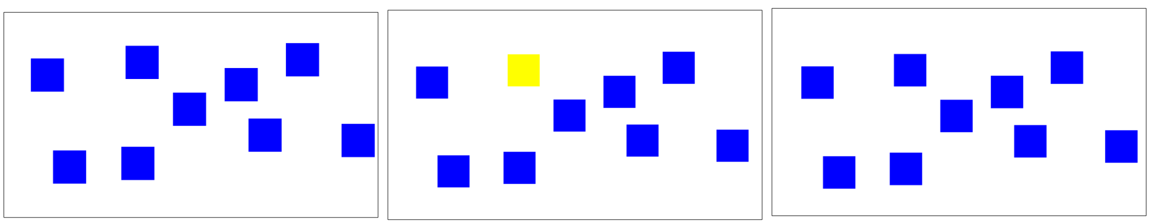
Implementation of the Reverse Corsi Block task follows Brunetti, Del Gatto, and Delogu (2014). For each trial, nine blue blocks appear in random locations on the screen. They take turns lighting up. Respondents are then asked to tap the blocks in reverse order of how they lit up (see Figure A9). For each element in the sequence, if the respondent taps on the correct block, it turns green and the respondent can proceed to tap the next block in the sequence. If the respondent taps any other block, it flashes red and the respondent moves to the next trial. The first trial sequence contains two elements. For each sequence the respondent gets completely correct, the sequence length increases by one.

Figure A9: Corsi Stimuli

(a) Blocks appear in random positions

(b) Blocks light up yellow randomly

(c) Respondents tap blocks in reverse order



Note: This figure shows the three stages of the reverse Corsi blocks test. The test is designed to measure working memory. First nine blocks appear in random positions. They then light up in a random sequence. Respondents must then tap the blocks in the reverse order of how they lit up. After each correct trial, the length of the sequence increases by one, and after every incorrect trial, the length of the sequence decreases by one down to a minimum of two elements.

C.2 Hearts and Flowers

Implementation of the Hearts and Flowers task follows the “dots" task outlined by Davidson et al. (2006). Respondents see a fixation dot in the center of their screen with blue boxes on the left and right. Respondents then see a sequence of hearts and flowers appear on the boxes. For each trial, respondents must press either the “Q" or “P" key. When a heart appears, respondents must press the key on the same side as the heart. While when a flower appears, respondents must press the key on the opposite side (see Figure A10).

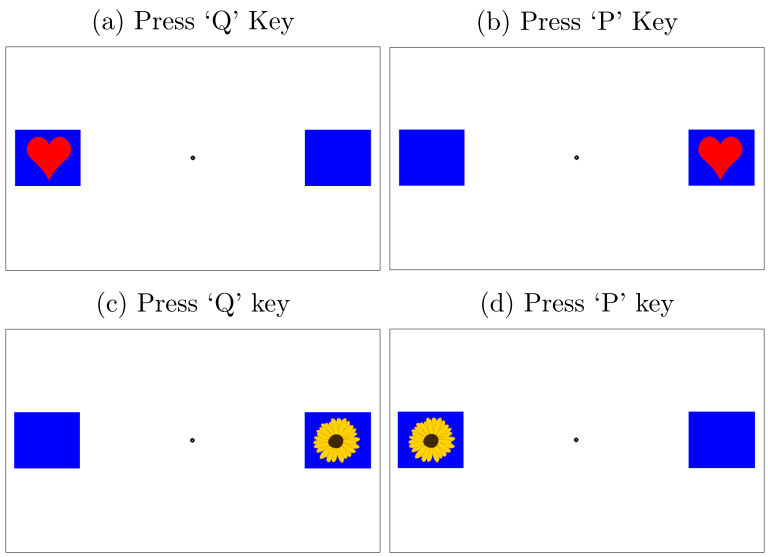


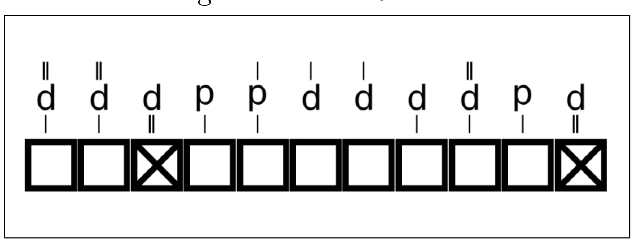
Figure A10: Hearts and Flowers Possible Stimuli and Responses

Note: The figure shows the four possible stimuli and responses for the hearts and flowers test. The test is designed to assess inhibitory control. Respondents see a series of hearts and flowers appear on the blocks. When a flower appears, the respondent must press the key on the opposite side of the keyboard. When a heart appears, the respondent must press the key on the same side of the keyboard.

C.3 d2 Attention Task

The d2 task follows the general instructions outlined in Bates and Lemay Jr. (2004) and Brickenkamp and Zillmer (1998). For each trial, eleven letters (either p or d) appear on the screen with between zero and two dashes above and zero and two dashes below for a total number of dashes between zero and four (see Figure A11). The respondent's job is to mark all of the d's with a total of two dashes by tapping the box below the letter. After 5106 ms, the trial ends. Until that time has elapsed, respondents can un-mark and re-mark letters as they please. Another set of eleven letters appears after 500 ms.

Figure A11: d2 Stimuli



Note: The figure shows an example of a trial from the d2 test. The test is designed to assess attention. Respondents see a series of d's and p's with up to two lines below and above. They must tap the boxes below all d's with a total of two dashes before the trial ends.