Cooking, health, and daily exposure to pollution spikes

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Abstract

We collect high-frequency individual pollution exposure and time use data to identify how daily economic activities such as charcoal cooking drive spikes in pollution exposure among 700 individuals in Kenya. Leveraging experimental variation we find that improved stoves reduce PM2.5 spikes while cooking by $52\mu g/m^3$ (42%) and cause a 0.24 standard deviation reduction in self-reported respiratory symptoms. However, even after three years of daily use, we find no clinical health improvements in blood pressure or medical diagnoses; this may be because we detect no impact on average exposure. Clinical health improvements may require reductions in ambient concentrations.

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1 Introduction

Air pollution is responsible for 7–9 million premature deaths annually (10-15% of all deaths), making it "the single biggest environmental threat to human health" (Global Burden of Disease, 2017; WHO, 2021). Specifically, research has shown that high average concentrations harm long-run clinical health and mortality.[1] However, many routine economic activities cause large but only brief spikes in exposure: two individuals with identical average exposure may experience very different within-day exposure (Figure 1 provides an example). What are the health impacts of repeated spikes in air pollution, often experienced on a daily basis, for years on end? Regulatory agencies and policy-makers alike are debating this question, both within and outside the U.S., for example in the contexts of cooking and transportation, two ubiquitous sources of daily pollution spikes (EPA, 2023; WHO, 2021).

The dearth of evidence on this topic results in part from the lack of high-frequency data on how individual-level behavior generates pollution spikes, and on how severely individuals are exposed to these spikes. This is difficult to observe because economic activity, human behavior, and demographic structures can all cause an individual's realized exposure to differ substantially from data captured through regulatory or other stationary monitoring. Studying the topic also requires a plausibly random reduction in pollution spikes, that persists daily, for multiple years in a row.

We generate causal evidence on this subject in the context of cooking. More than three billion people cook using polluting fuels such as charcoal (WB, 2020). We offer 1,000 charcoal cookstove users in Nairobi—who on average cook for around two hours per day—randomized subsidies and access to credit for an improved stove that uses 40% less charcoal. We follow up with study participants after 3.5 years of daily use—importantly, 86% of respondents still have the same adoption status. To characterize impacts on the distribution of individuals' realized pollution exposure, respondents carry a backpack containing high-frequency pollution monitoring devices for 48 hours. A complementary time use survey records each respondent's activities—and whether they were indoors—during each of those 48 hours. Informed by the pathophysiologic pathways linking pollution to cardiopulmonary disease, clinical health outcomes include blood pressure, pulse oxygen, and self-reported respiratory and other diagnoses (Seaton et al., 1995; Pope, 2000). We also collect detailed self-reports on health symptoms for adults and children.

Our first finding is that the improved stove reduces pollution spikes during cooking hours by 42%. For the control group, the average cooking spike (which we measure as the 99^{th} per-

[1] Greenstone and Hanna (2014), Schlenker and Walker (2015), Chang et al. (2016), Isen, Rossin-Slater, and Walker (2017), Hansman, Hjort, and León (2018), Deryugina et al. (2019), Wen and Burke (2022), Clay, Lewis, and Severnini (2022), and Deryugina and Reif (2023).

centile of 10-minute measurements during cooking hours) increases pollution by 125 $\mu g/m^3$ relative to daily median exposure of 25 $\mu g/m^3$. Improved stoves reduce this by 52 $\mu g/m^3$.[2]

These reductions provide important health benefits. We estimate that improved stove adoption causes a statistically significant 0.24 standard deviation reduction in an index of self-reported respiratory symptoms such as headache and cough. Several robustness checks provide evidence that experimenter demand is unlikely to explain this, at least not entirely.

However, we see no impacts on clinical health outcomes such as blood pressure, blood oxygen, and medical diagnoses (including pneumonia). Even after 3.5 years of significant reductions in daily pollution spikes we can rule out a 0.14 SD or greater reduction in health diagnoses and a 6 mm Hg or greater reduction in systolic blood pressure (SBP). For comparison, smoking a cigarette acutely increases SBP by 20 mm HG (Cohen and Townsend, 2009). Combining our estimates with evidence from the medical literature we can reject a 12% or greater decrease in major cardiovascular events. Robustness checks indicate that the lack of clinical health impacts is not driven by measurement error or statistical noise: for example, we find a strong correlation between blood pressure and self-reported medical diagnoses.

These results can be reconciled by looking at how the intervention changed the distribution of pollution. While there was a significant decrease in spikes while cooking, study participants only cook for two hours per day on average (9% of the time). Thus, the 33% reduction in mean pollution exposure during cooking hours translates to an approximately 2.1% reduction in overall average pollution, which we cannot statistically distinguish from zero.

Taken together, the evidence is consistent with pollution spikes driving short-term respiratory symptoms and clinical health being driven by average exposure. This would imply that individuals have limited means to improve their own health by adopting improved stoves: two-thirds of respondents experience daily average pollution between 20–49 $\mu g/m^3$ (AQI 70-135), and we cannot reject the null that cookstove adoption does not change this. We present descriptive evidence supporting this interpretation: for example, self-reported symptoms correlate with pollution spikes but not with average concentrations. Participants' beliefs about the stove's potential health benefits are also consistent with this interpretation. At baseline, 37% of respondents believed that adoption of the improved stove would have no impact on their health, and 34% believed it would have a small impact. These beliefs were not correlated with baseline willingness-to-pay—unlike beliefs about financial savings—suggesting health improvements were not a key feature of the stove. While clinical health benefits could emerge over a longer time horizon, they may require a reduction in average pollution exposure, for example by regulating ambient pollution levels. Improved stoves may

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

improve health more in rural areas, or less in cities with even higher ambient air pollution.[3]

This research advances the literature in several ways. Collecting individual exposure measurements of particulate matter smaller than $2.5\mu m$ (PM2.5) and carbon monoxide (CO) on a minute-by-minute basis for 48 hours, which we map to hourly time use data, allows us to generate individual distributions of pollution exposure. Doing so in a high-stakes, non-laboratory setting allows us to understand how routine economic activities and human behavior drive realized pollution exposure. We combine this with experimental variation that reduces a key source of daily pollution spikes persistently for 3.5 years, and collect clinical and self-reported health outcomes to causally estimate the long-term impact of these reductions.

Much existing research on the health impacts of air pollution evaluates changes in mean daily concentrations collected by stationary monitors.[4] However, recent debates have heightened concerns about additional moments of the air pollution distribution, for example in relation to induction stoves (The Guardian, 2023) and wildfire smoke (Scientific American, 2024). The impacts of repeated transient spikes could differ substantially from daily averages and one-off spikes because of the non-linearity in health impacts that many papers find. However, these moments are difficult to observe because individual exposure can differ substantially from concentrations measured by stationary monitors: Pitt, Rosenzweig, and Hassan (2010) for example discuss how family structure affects cooking pollution exposure. Papers studying the impacts of sub-24 hour pollution shocks and other higher frequency moments of the pollution distribution tend to study one-off shocks rather than repeated daily spikes.[5] A key feature of our paper is that the large impacts on pollution spikes have negligible impacts on average exposure, allowing us to study the impacts of spikes per se.

The dearth of research on recurrent spikes in exposure impedes the optimal design of costly environmental regulations. Most countries—as well as the WHO—only regulate PM2.5 using annual and 24-hour averages or extremes (Nazarenko, Pal, and Ariya (2021) in WHO Bulletin). The regulation of daily PM2.5 spikes is subject to ongoing debate: the U.S. Environmental Protection Agency's recent review of the National Ambient Air Quality Standards notes that much research on the impacts of short-term spikes evaluates the immediate im-

[3]PM2.5 averages 13 $\mu g/m^3$ in Rome, 30 $\mu g/m^3$ in Accra, and 99 $\mu g/m^3$ in Delhi (IQAir, 2019).

[4]See footnote 1 for research on this topic. Papers that study non-linearity in the dose-response function often study concavity in daily averages (He, Fan, and Zhou, 2016; La Nauze and Severnini, 2021; Gong et al., 2023). Those that study how regulations and firm actions affect pollution spikes (also known as 'episodic pollution') often do not measure subsequent health outcomes (Henderson, 1996; Caplan and Acharya, 2019; Cropper et al., 2014; Cutter and Neidell, 2009).

[5]In the economics literature, see Adhvaryu, Kala, and Nyshadham (2022), Künn, Palacios, and Pestel (2023), Ebenstein, Lavy, and Roth (2016), and Archsmith, Heyes, and Saberian (2018). Experimental papers on the health impacts of short-term pollution spikes include, for example, Kubesch et al. (2015), Soppa et al. (2014), Kocot et al. (2020), Fedak et al. (2019), and Shehab and Pope (2019).

pacts of a single spike, rather repeated daily exposure (EPA, 2023).

More than 90% of pollution-related deaths occur in low- and middle-income countries (WHO, 2021). For the three billion people lacking access to improved stoves (World Bank (WB), 2020), the use of traditional cookstoves is a key source of transient pollution spikes. Extensive research has associated a wide range of health problems with energy-intensive cookstove usage (WHO, 2021; Lancet, 2017). However, the evidence is far from conclusive. Most papers are correlational rather than causal, and many randomized trials study adoption rather than on the health impacts of improved cookstoves.[6] A recent *Lancet* meta-analysis 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*." The large RESPIRE and HAPIN trials make valuable advancements to this literature (Smith et al., 2011; Clasen et al., 2022). However, these trials took place rural communities; in a 2018 review of the cookstove literature, Thakur et al. (2018) identified no urban papers.[7] There is almost no evidence evaluating cooking exposure in contexts with high ambient pollution, even though the one billion urban poor who live in slums are chronically exposed to both: 80% of urban 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.[8] 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

Particulate matter (PM) is generally defined by size rather than by chemical make-up: PM2.5 refers to any particulate smaller than 2.5 μm in diameter. The chemical content of PM varies across locations, hour of day, and day of year. In Nairobi, PM consists primarily of organic carbon, dust, and sea salt (Figure A1). Charcoal burning can contribute to both organic carbon and black carbon, as can the burning of most types of fossil fuel (diesel, petrol, and

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

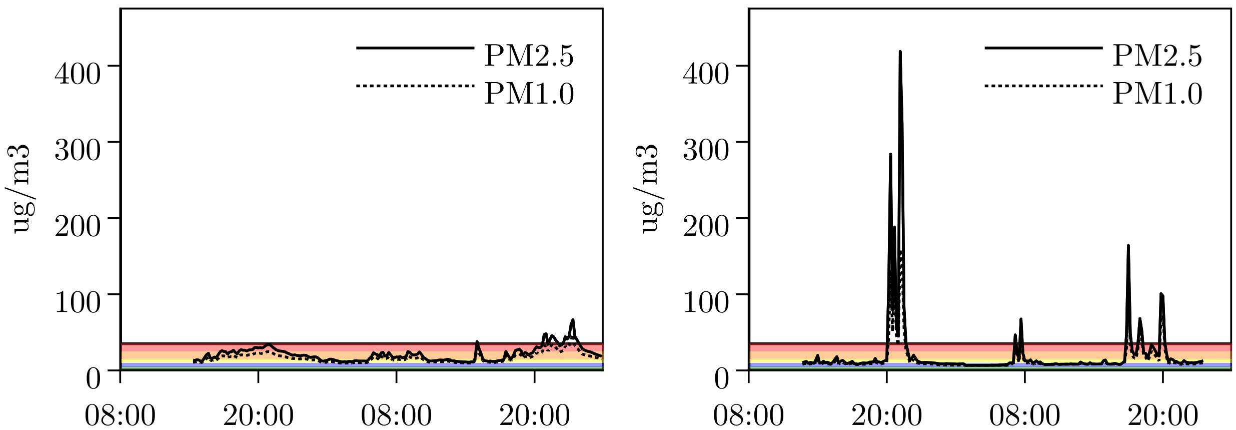
[7]More recently, Alexander et al. (2018) measured spikes and duration of exposure to estimate the pollution and health impacts of improved stove adoption in an urban setting, but their sample is restricted to pregnant women, they do not separately measure ambient pollution, and they examine relatively modest variation in air pollution (a 5–13% reduction in PM2.5 spikes, and no impact on the mean). For the interested reader, Table B1 provides an overview of the causal evidence.

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

coal) and forest products.

Pope et al. (2018) document average roadside PM2.5 levels in Nairobi, Kenya of 37 $\mu g/m^3$ and average urban background levels of 25 $\mu g/m^3$. This is roughly in the middle tercile of global urban pollution distributions: PM2.5 concentrations average 13 $\mu g/m^3$ in Los Angeles and Rome and 30 $\mu g/m^3$ in Kampala and Accra, but 49 $\mu g/m^3$ in Jakarta and 99 $\mu g/m^3$ in Delhi (IQAir, 2019). Figure 1 displays daily PM2.5 patterns collected in Nairobi, Kenya by two study participants.

Figure 1: Daily pollution for two study participants, both with average exposure of 21 $\mu g/m^3$



Ten minute averages (of 2-minute frequency measurements) collected by two study participants, both residing in Nairobi, Kenya, carrying Purple Air II Air Quality Sensors over 48 hours. Both have average daily PM2.5 exposure of 21 $\mu g/m^3$. The black horizontal line marks 35 $\mu g/m^3$, the WHO's least stringent interim target. The green, blue, yellow, orange, and red bars indicate the World Health Organization's recommended air pollution targets, ranging from <5 $\mu g/m^3$ to 25–35 $\mu g/m^3$, its most to least stringent recommended targets, respectively (WHO, 2021). Section 3.3 provides more detail on data collection.

2.1 Transient spikes in air pollution

Most domestic governments—as well as the WHO—only provide PM2.5 standards for annual and 24-hour average concentrations.[9] Whether to regulate spikes is subject to ongoing policy debate, for example in the recent U.S. Environmental Protection Agency evaluation of the National Ambient Air Quality Standards (NAAQS) for Particulate Matter (EPA, 2023). 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).

In many low- and middle-income countries (LMICs), indoor cooking is a key source

[9] Russia limits 20-minute PM2.5 averages, making it the only country that regulates a shorter interval.

of transient air pollution spikes. More than 4 billion people still do not have access to clean cooking technologies (WB, 2020), causing millions of deaths each year (WHO, 2017; Pattanayak et al., 2019; Bailis et al., 2015). This includes many who live in cities: 80% of households living in African cities still primarily use biomass (wood or charcoal) for cooking, and three billion people are expected to live in slums in Africa and Asia by 2050 (FAO, 2017; WHO, 2021; UN, 2022). As a result, urban LMIC residents suffer disproportionately from both high average pollution concentrations and even higher transient spikes.

2.2 Cookstoves in Kenya

Two-thirds of Kenyan households rely on biomass as their primary cooking fuel (KNBS, 2019; WB, 2019). Around 42% of Kenyan households use a Kenyan Ceramic Jiko (KCJ, or just *jiko*) 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, even compared with the WHO's least stringent air pollution target of $<35\ \mu g/m^3$, let alone its most stringent target of $<5\ \mu g/m^3$ (WHO, 2021).

Figure 2 displays a *jiko* as well as the Jikokoa, an energy efficient charcoal stove produced by Burn Manufacturing ('Burn'), which has sold more than four million energy efficient cookstoves since 2014. Berkouwer and Dean (2022a) provide more detail on charcoal consumption, barriers to adoption, and access to credit among potential adopters in Nairobi.

Figure 2: 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.

The primary difference between the two stoves is that the Jikokoa's main charcoal combustion chamber is constructed using improved insulation material and designed for optimized fuel-air mixing (Berkouwer and Dean, 2022a). Designed and tested by laboratories in Nairobi and Berkeley, the Jikokoa is made of a metal alloy that better withstands heat, and a layer of ceramic wool insulates the chamber to cut heat loss. Parts are made to strict specifications, and components fit tightly to minimize air leakage. 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.

2.3 Existing health measurement methodologies

An extensive public health literature informed the selection of health-related outcome variables. Kubesch et al. (2015), Chang 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). 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). 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.

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.[10] Finally, oximetry readings have been found to be a cost-effective approach to screening for respiratory infections (Floyd et al., 2015; Van Son and Eti, 2021; National Library of Medicine, 2021).

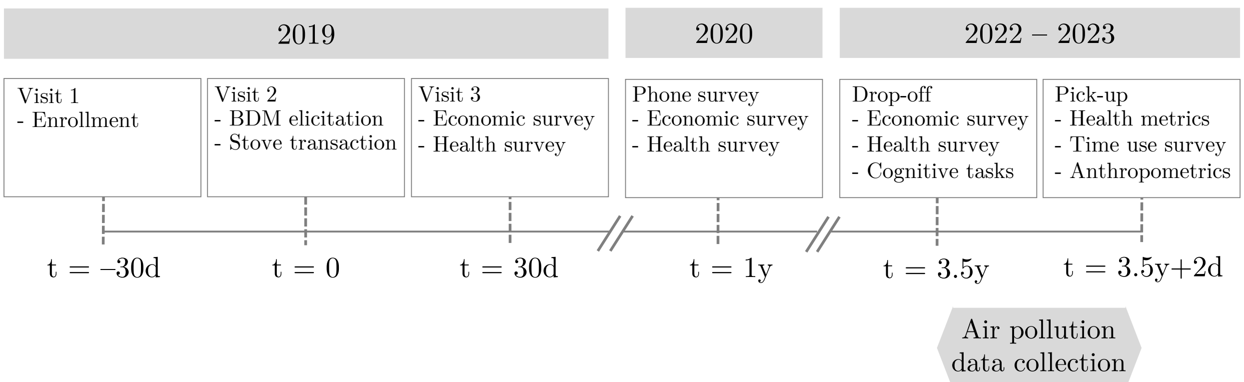
[10] For example, UNICEF MICS6 (2020) identifies ARI if a child had fast, short, rapid breaths or difficulty breathing in combination with chest problems.

One challenge when trying to identify the health impacts of improved stoves is that adopters may not use the improved stove consistently (e.g. Hanna, Duflo, and Greenstone, 2016; Beltramo and Levine, 2013). Berkouwer and Dean (2022a) rule 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 3 presents an overview.

Figure 3: Timeline of field activities



Participants who adopted the stove did so during the main visit ($t = 0$). For 89% of respondents the long-term endline was conducted 3.4–3.7 years after the main visit. Child anthropometrics were collected on either drop-off or pickup depending on presence. Due to health restrictions, the 2020 survey was conducted by phone.

In the baseline enrolment survey conducted April-May 2019 (visit 1), enumerators enrolled respondents residing in urban settlement areas around Nairobi, Kenya who used a traditional charcoal stove as their primary daily cooking technology, who were the primary cookstove user in their household, and who spent at least \$3 per week buying charcoal. In terms of housing quality and type, and ventilation between indoor and outdoor air, respondents' housing characteristics are similar to those of many other densely populated neighborhoods in large cities in low- and middle-income countries.

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 (Usmani, Steele, and Jeuland, 2017; Hooper et al., 2018). Specifically, in an unprompted manner they asked respondents what they perceived to be the main benefits of the improved stove—62% stated 'reduced smoke' (95% 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 the improved stove might improve their health.

During the main visit (visit 2)—which took place approximately one month after each respondent's baseline visit and was completed by 955 respondents—each respondent was given an opportunity to buy the stove at a subsidized price (Section 3.1 discusses the subsidy randomization in more detail). Of the 955 respondents who completed the main visit, 570 (60%) adopted the improved stove.

In June–July 2019, approximately one month after the main visit, enumerators conducted a short-term follow-up survey (visit 3). In 2020, approximately 16 months after the main visit, enumerators conducted a medium-term follow-up survey.[11] Both follow-up surveys included socio-economic questions as well as the same health symptoms questions asked during the baseline surveys.

In 2022–2023 enumerators conducted a long-term endline survey round, which consisted of two surveys, the second approximately 48 hours after the first. The surveys were designed to take rigorous quantitative measurements of air pollution exposure and physical health. 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. Enumerators were able to reach 775 and successfully surveyed 702 (75%) of the 942 respondents they attempted to reach. Recent demolitions of informal settlements in Nairobi contributed to imperfect follow-up (The Star, 2023), but attrition is balanced by treatment assignment, take-up, and baseline health (Section 4.7 provides more analysis on attrition). Of the 702 respondents, 639 still lived in or near the original study areas, 53 had moved to rural areas, and 10 had moved elsewhere in Nairobi. 95% of respondents were surveyed between 3.4–3.7 years after the main visit. Table 1 presents summary statistics collected during the endline survey.

3.1 Causal identification

The Jikokoa cost $40 in stores at the time. Each respondent was randomly assigned a subsidy between $10-39, stratified on baseline charcoal usage (Figure A2 shows the distribution of prices). The subsidy treatment 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 the main visit, enumerators used a Becker, Degroot, and Marschak (1964) mech-

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

Table 1: 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.

anism (BDM) to elicit WTP for the improved 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 assigned price (the market price of $40 minus the randomly assigned subsidy) then adopted the stove.[12]

The credit treatment doubled WTP, while the attention treatment had no effect on WTP (Figure A5). Among those in both the high subsidy and the credit treatment group 93% adopted the improved stove, 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

[12] 98.6% of respondents for whom this was the case actually adopted the stove.

the randomly assigned subsidy, the credit treatment assignment, and their interaction as instruments for adoption. We report weak instrument F-statistics where relevant, but the first stage is generally strong.

3.2 Time use and behavior

To match high-frequency pollution data to specific activities such as cooking or commuting, the second endline survey included a time use module asking which activity or activities the respondent was engaged in for each hour between the two surveys, whether they were primarily 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 slightly more in the mornings and charcoal stoves used more in the evenings (Figure A3).[13]

Respondents are indoors on average 89% of hours spent cooking, but there is some heterogeneity correlated with stove usage. For the 278 respondents who report using an LPG or electric stove at least once in the time use survey, on average only 5% of hours spent cooking with such a stove are spent outdoors. Conversely, for the nearly 500 respondents who report using a wood or charcoal stove at least once in the time use survey, more than 20% of hours spent cooking with such a stove are spent outdoors. Respondents may be choosing to cook indoors when using a relatively cleaner stove, which would limit the reduction in pollution exposure caused by the improved stove, as emissions are more likely to build up indoors. All of our results on the impact of improved cookstove adoption should be interpreted as factoring in any accompanying behavior changes such as location choice, or opening doors or windows in order to increase ventilation, which have been shown to matter (Lenz et al., 2023). That said, we do not detect an impact of improved cookstove adoption on the propensity to cook or to cook indoors (Table B6).

3.3 Measuring air pollution exposure concentrations

We use two devices to measure air pollution. A Purple Air II Air Quality Sensor (PA-II) takes one measurement of Particulate Matter (PM) every two minutes,[14] and a Lascar

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

[14]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 Ward et al. (2021) and Giordano 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).

EL-USB-CO Data Logger takes one measurement of Carbon Monoxide (CO) per minute (Figure A6 depicts the two devices).[15] 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 A7). For this reason we include device fixed effects in all regressions.[16]

Air pollution exposure varies considerably not only by cookstove usage but by user behavior (Pitt, Rosenzweig, and Hassan (2010), for example, discuss how household structures affect exposure). Following best practices from the public health and air pollution monitoring literature (Gordon et al., 2014; Gould et al., 2022; Chillrud et al., 2021; Burrowes et al., 2020), and using procedures developed by the Berkeley Air Monitoring Group (Johnson et al., 2021), we therefore collect personal exposure as experienced by respondents rather than conducting stationary monitoring of kitchen concentrations. During the first follow-up survey we provided each respondent with a small mesh backpack containing the two devices (Panels C and D of Figure A6). 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. During the second follow-up survey 48 hours later the enumerators 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.[17] Collecting pollution exposure over a 48-hour period captures pollution generated by the respondent as well as ambient pollution generated by industrial facilities, traffic, or other sources in urban Nairobi. Figure 4 displays respondents' average air pollution exposure over the 48 hours, by their residential location. For most respondents, average PM2.5 is well above the WHO's air quality limits.

Enumerators did not observe significant hesitancy from participants about wearing the backpacks. Of the 43 respondents for whom air pollution data are missing, 36 had stated in advance that they only had time to complete one survey and as a result were never asked to receive the devices.[18] 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, but enumerators reported generally high backpack wearing.[19]

[15] 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.

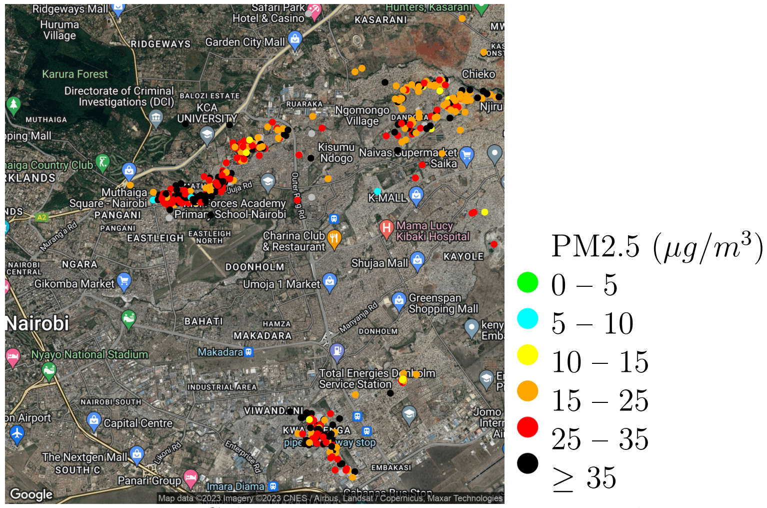
[16] Interacting device fixed effects with a linear time trends could account for heterogeneous trends across devices. This increases standard errors but does not qualitatively change the results.

[17] 85% of respondents held the device between 45–50 hours.

[18] The remaining nine all agreed to receive the backpack, but the data were unusable for technical reasons.

[19] 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 more severe widespread non-compliance.

Figure 4: 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 is 5 $\mu g/m^3$ (WHO, 2021). WHO interim targets 1 through 4 correspond to 10, 15, 25, and 35 $\mu g/m^3$. 63 survey respondents reside outside the depicted area.

Panel A of Figure 5 shows how average pollution varies over the hours of the day, by whether or not the respondent owned a Jikokoa as of the 2022–2023 survey. 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. Average PM2.5 concentrations are highest in hours when participants self-report cooking (particularly with biomass stoves), and lowest in the hours when sleeping (Table B3). Emissions in the 60 to 30 minutes prior to the emissions peak is approximately similar across stoves, but the return to baseline levels takes significantly longer for dirtier biomass stoves than it does for cleaner stoves (Figure A9). We do not observe any meaningful seasonal heterogeneity in air pollution over our sample period.

To better understand the distribution of pollution we compute average exposure during each 10-minute window for each respondent in our data. Panel B of Figure 5 shows the cumulative distributions of respondents' 50th and 99th percentile 10-minute averages. Median 10-minute average is below 50 $\mu g/m^3$ for 89% of respondents, but the 99th percentile exceeds 100 $\mu g/m^3$ for half of respondents, and exceeds 200 $\mu g/m^3$ for 23% of respondents. This provides the first evidence that within-day variation is statistically and economically significant.

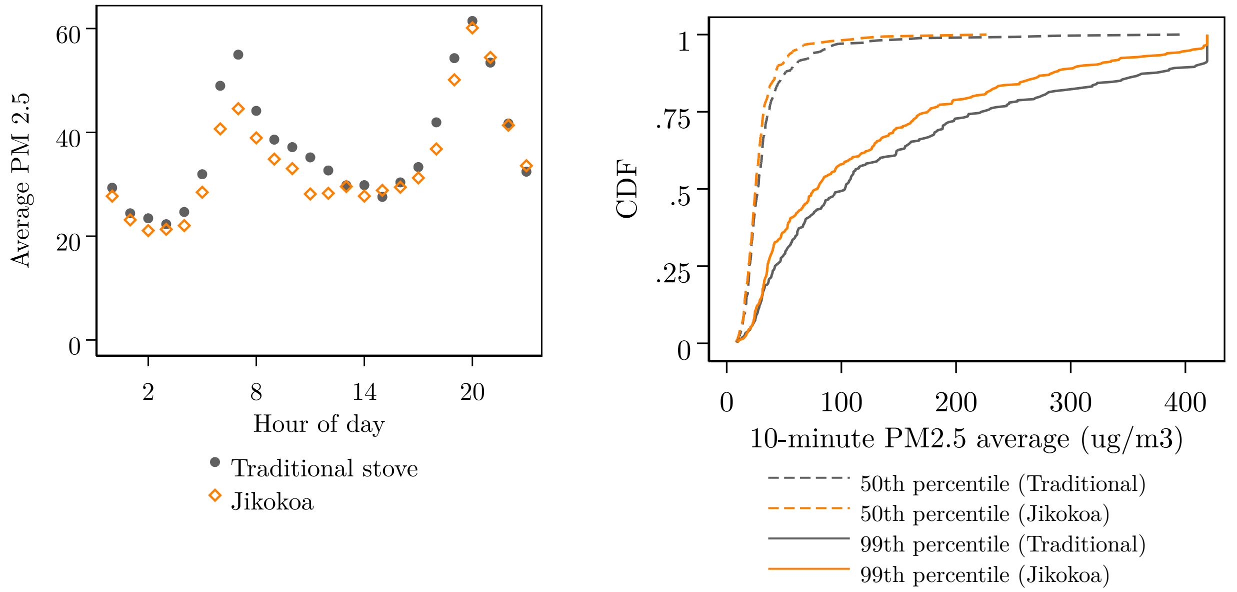
3.4 Measuring physical health

Informed by a medical literature studying the pathophysiologic mechanisms linking particulate matter with cardiac and pulmonary disease (Seaton et al., 1995; Pope, 2000), we focus

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

A) Hourly averages over the day

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



Panel A shows average PM2.5 air pollution, by hour and endline improved stove ownership, as collected by respondents wearing backpacks for on average 48 hours. Figure A8 presents the same for PM1.0 and CO.

on blood pressure, blood oxygen, and medical diagnoses of key respiratory diseases.

Enumerators record systolic and diastolic blood pressures using a sphygmomanometer, following procedures set by the Centers for Disease Control and Prevention NHANES (2019).[20] 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 ($\geq$ 140/90 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.[21] They also ask 10 yes/no questions about whether a medical professional had diagnosed the respondent with various medical diagnoses (including pneumonia, asthma, or other lung disease), of which we only use diagnoses that were made in the past three years (since the original experiment) in the analysis.

Following the methodology from the public health literature (see for example Tielsch et al., 2016; Smith-Sivertsen et al., 2009; Checkley et al., 2021 and others), the survey fur-

[20] 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.

[21] While we considered collecting spirometry or peak expiratory flow data, 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.

thermore asks a large set of self-reported health questions. This includes 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 inquired about recent pregnancies, birth outcomes, and any recent newborns' weight and length. We use these self-reports to generate several standardized physical health indices.

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

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 1 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 respondents were surveyed.

3.5 Measuring 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 (Brickenkamp and Zillmer, 1998; Bates and Lemay Jr., 2004). Appendix C provides detail on these assessments. The analysis uses a standardized adult cognitive ability index that combines these three outcomes.

4 Causal impacts

To estimate the causal effect of improved stove adoption on pollution spikes and health, we use an instrumental variables (IV) approach where we use the randomly assigned stove price, the randomly assigned credit treatment status, and their interaction as instruments for stove ownership. These treatments had a statistically and economically large effect on stove adoption in Berkouwer and Dean (2022a).[22] Since both are randomly assigned, this regression

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

identifies the causal effect of stove adoption on the outcomes of interest. Regressions include socioeconomic controls and fixed effects as indicated.[23]

The 'stove adoption' dummy 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 subsidies and credit on stove ownership and usage

Panel A of Table 2 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 still do not own one during the long term endline, and 83% of respondents who adopted a Jikokoa initially still own one three years later. This persistence generates a strong first stage, with weak IV F-statistics between 20 and 50 depending on the specification (Table B4).

The median household owns two stove types, indicating some degree of fuel stacking. Liquefied petroleum gas (LPG) usage has risen sharply in recent years, particularly in Nairobi where 60% of respondents report owning an LPG stove (compared with 40% of those who live elsewhere), potentially as a result of a government LPG subsidy program (IEA, 2022). This paper's estimates of pollution and health impacts 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 LPG, bio-ethanol, or electric stove ownership, though we cannot rule out modest increases. We thus find limited evidence of the 'energy ladder' mechanism where improved stove adoption can act as a stepping stone (Hanna and Oliva, 2015), nor

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

Table 2: 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)	
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) on outcomes from 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 B5 presents additional socio-economic outcomes.

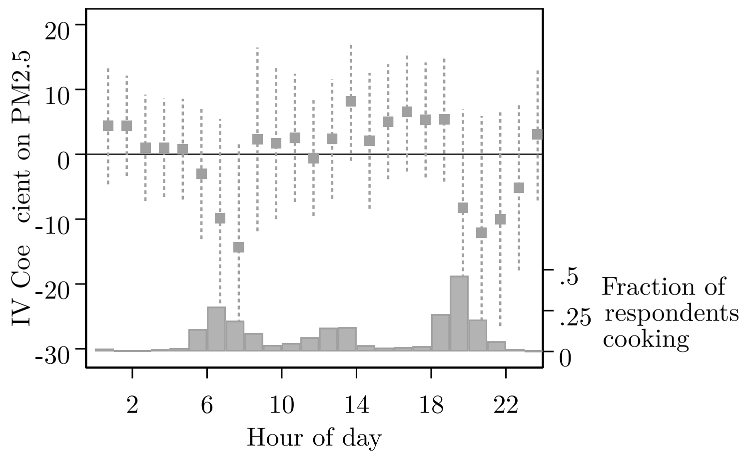
of the converse, that adoption of an intermediary technology can slow adoption of an even more improved technology (Armitage, 2022; Hornbeck et al., 2024).

Improved stove adoption does not appear to impact time spent cooking per day, nor the propensity to cook indoors (Table B6). It slightly increases the propensity to cook Githeri (a common maize and beans dish) but has no other impacts on foods cooked (Table B7).

4.2 Impacts of stove ownership on air pollution

We use the same IV approach to estimate the causal impact of stove adoption on air pollution for each hour of the day. Figure 6 shows that the impact varies significantly across hours in the day. Improved stove ownership reduces air pollution between 5–8am and 7–10pm—when respondents report to be cooking—but not during other hours of the day.[24]

Figure 6: Impact of Jikokoa ownership on average hourly PM2.5 (in $\mu g/m^3$)



Coefficients from a single instrumental variables regression that uses subsidy, credit treatment status, their interaction, and their interaction with hour of day dummies as instruments to estimate the causal impact of Jikokoa ownership on PM2.5 exposure (with socioeconomic controls and panel fixed effects). The gray bars report the fraction of respondents who report cooking during any given hour in the time use survey. Table 3 pools the data to improve statistical power. Figure A11 presents the OLS version.

To improve statistical power, Table 3 aggregates PM2.5 exposure data for each individual. We use the same IV approach to estimate the causal impact of stove adoption on four key moments of PM2.5 pollution exposure: median exposure (column 1), mean exposure (column 2), the maximum hourly average (column 3), and the 99th percentile of 10-minute averages (column 4). Panel A includes all 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 (for robustness, Table B9 presents results on all non-cooking hours and on cooking hours defined uniformly as 6–8am and 6–9pm).

Two key patterns emerge. First, improved stove adoption causes 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 42% reduction in the marginal emissions increase from cooking (over median non-cooking exposure) when compared with

[24]Pollution impacts occur slightly after cooking, possibly because smoke can persist for some time after the user stops cooking, or because respondents start lighting the stove some time before actually cooking and do not consider this cooking in the time use survey.

Table 3: Causal impact of cookstove adoption on PM2.5 exposure

Panel A) All hours

	(1) Median	(2) Mean	(3) Max Hour	(4) 99th
Own Jikokoa	0.1	-0.8	-16.4	-8.3
	(1.7)	(3.4)	(19.0)	(23.0)
Control Mean	25.2	37.8	153.3	200.3
Weak IV F-Statistic	53	53	53	53
Observations	651	651	651	651

Panel B) When self-reporting cooking

	(1) Median	(2) Mean	(3) Max Hour	(4) 99th
Own Jikokoa	-11.0**	-16.6***	-31.0**	-52.0**
	(5.2)	(6.4)	(15.4)	(22.5)
Control Mean	35.9	49.7	92.6	150.3
Weak IV F-Statistic	48	48	48	48
Observations	598	598	595	598

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. Column (1) uses median exposure, (2) uses mean exposure, (3) uses maximum 1-hour average exposure, and (4) uses 99th percentile of 10-min average exposure. Of the 702 respondents surveyed, 651 consented to having a PA-II device (Section 4.7 discusses attrition); some of them never self-reported cooking. Regressions include socioeconomic controls and a fixed effect for the specific PA-II device that respondent used. Table B8 presents the same for carbon monoxide. Table B9 presents the same for when self-reporting not cooking and for the hours between 6–8am and 6–9pm. Table B10 presents all outcomes in logs.

the control group.[25] This mirrors the 41% reduction in charcoal expenditures identified in Table 2: PM2.5 emissions from cooking appear to decrease proportionally to charcoal usage. Columns 3 and 4 of Panel A show that there is a smaller reduction in max hourly and 99th percentile of 10-minute pollution over all hours of the day, which includes spikes generated for example by traffic. While cooking with a traditional charcoal jiko might generate larger spikes than commuting, this may not be the case for cooking with a Jikokoa, such that for many adopters the largest spikes no longer occur during cooking. These patterns are economically and statistically similar when the data are analyzed in logs (Table B10).

Second, despite large emissions reductions during cooking, there is only a 2% reduction in aggregate average exposure, and this reduction is not statistically significantly different from zero (Column 2 of Panel A in Table 3). This appears to be because respondents cook for only 9% of the day (2 hours) on average, and continue to experience median non-cooking

[25] To estimate the marginal emissions from cooking we first estimate typical ambient exposure as the average across control participants of their median 10-minute windows; this is 25.2 $\mu g/m^3$. We then estimate typical cooking exposure as the average across control participants of their 99th percentile 10-minute windows during hours while cooking; this is 150.3 $\mu g/m^3$. Differencing these two estimates gives an estimated marginal effect of cooking of 125.1 $\mu g/m^3$.

exposure to PM2.5 of around 25 $\mu g/m^3$ during the remaining time. In line with this, we cannot reject that the coefficient in Column (2) of Panel A is exactly 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.

It is worth noting that many people likely move away from their stove or increase ventilation at least sometimes while cooking, which reduces average cooking concentrations measured by personal exposure devices. While realized pollution exposure is the relevant object for policy and health research, the reduction in pollution caused by improved stove adoption might have been larger if measured using stationary stove monitors. The reductions measured by personal monitors could thus be considered a lower bound on total emissions reductions.

Cooking hours tend to coincide with traffic patterns: both have a morning and an evening spike. Using hourly data on self-reported cooking activity and pollution allows us to include hour-of-day fixed effects in the regressions. However, this significantly reduces identifying variation since there is a strong correlation between hour of day and propensity to be cooking. We therefore estimate this regression using both IV and OLS specifications (Table B11). 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 significantly during self-reported cooking hours.

The lack of impact on average daily emissions stems in large part from the high ambient pollution that many urban areas experience. What might the reduction in pollution exposure be in rural areas, where ambient air pollution is on average 9 $\mu g/m^3$ (Pope et al., 2018)? We conduct a back-of-the-envelope calculation to estimate this. 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.[26] This suggests that even in rural areas, and under conservative assumptions, improved cooking technologies are unlikely to have a large impact on daily average exposure.

We see no impacts on CO (Table B8), in line with 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 oxygenation rate: higher oxygen inflow increases CO_2 production and reduces CO production while cooking. Per the company's engineers, 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.

Finally, we estimate the impacts of spending a specific amount of time above a certain

[26]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 4: 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 [1.00]	0.02 (0.17)	0.02 (0.13)	696
Number of non-respiratory health symptoms	1.09 [1.54]	-0.24 (0.25)	-0.18 (0.19)	702
Non-respiratory health symptom index	-0.00 [1.00]	-0.03 (0.19)	-0.03 (0.14)	702
Number of respiratory health symptoms	1.70 [1.76]	-0.48** (0.23)	-0.36** (0.17)	702
Respiratory health symptom index	-0.00 [1.00]	-0.24* (0.13)	-0.18* (0.10)	702
Health diagnoses index	0.00 [1.00]	0.13 (0.16)	0.10 (0.12)	702
Number of health diagnoses	0.30 [0.58]	0.13 (0.09)	0.10 (0.07)	702
Cognitive index	-0.00 [1.00]	-0.01 (0.15)	-0.02 (0.12)	587
Healthcare utilization index (spending and visits)	-0.00 [1.00]	0.08 (0.14)	0.05 (0.11)	702

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 B13, Table B14, Table B15, Table B16, and Table B17 present detailed results on the components of the diagnoses, respiratory symptoms, non-respiratory symptoms, cognitive, and healthcare utilization indices. Outcomes for children are presented in Table B18.

air pollution threshold, for different thresholds, mirroring common regulatory proposals (Table B12). This dramatically reduces the power of the estimation, as only movements across the threshold will generate a treatment effect. 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

How does the 42% reduction in cooking emissions spikes affect health? Table 4 estimates the impact of stove adoption on health outcomes, using the IV approach discussed above and controlling flexibly for age and linearly for other baseline socioeconomic outcomes. Column (2) uses 2022 Jikokoa ownership as the endogenous variable while Column (3) uses 2019 Jikokoa adoption. The first outcome is an index of clinical health measurements. 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.

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 B14 presents more detailed results on pollution-related symptoms). These results are unlikely to be driven by experimenter demand (Section 4.6 conducts a formal analysis on this). This reduction is sizeable, though smaller than the 0.56 standard deviation reduction in self-reported symptoms estimated using data from the one-year follow-up survey (Berkouwer and Dean, 2022a).

However, we identify no long-term health improvements in clinical outcomes such as blood oxygen, blood pressure, and self-reports about any diagnoses made by a medical professional during a hospital visit (Table B15 and Table B13 present more detailed results on non-pollution related symptoms and medical diagnoses, respectively). Specifically, we can reject that owning a stove at endline 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.

Table 5 presents the impacts on the individual components of the physiology index. To interpret these results 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 meta-analysis 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%. As another point of comparison, smoking a cigarette causes an acute increase in systolic blood pressure of 20 mm Hg, however the impact of smoking on weight loss complicates inference about the impact of smoking on long-term blood pressure through the respiratory channel per se (Cohen and Townsend, 2009).

It is worth noting that the lack of impact on these clinical outcomes is unlikely to be driven by measurement error or by lack of power: there is a strong correlation between self-reported health diagnoses and blood pressure and a weaker correlation with non-respiratory symptoms (Table B19). This suggests these measures contain a meaningful signal of clinical health.

We find no effect on the number of hospital visits, hospital-related expenditures, or any of the cognition outcomes (Table B16).[27] Finally, we see no impacts on childrens' outcomes. We

[27]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

Table 5: 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 IV regression where randomly assigned price, credit treatment status, and their interaction are used as instruments for endline Jikokoa ownership. Regressions include socioeconomic controls.

cannot detect a statistically significant impact on a range of child health outcomes, including child anthropometrics (raw and WHO growth standard-adjusted z-scores of weight, height, and arm circumference), a range of self- or parent-reported symptoms, and two types of attempted pneumonia diagnoses (Table B18), neither among children under 10 nor when restricting the sample to children under 6, who are more likely to stay at home during the day.

Participants' baseline beliefs about the stove's health benefits on average lines up well with these findings. At baseline, 37% of respondents believed that adoption of the improved stove would have no impact on their health, 34% believed it would have a small or medium impact, and only 29% believed it would have a large or very large impact. Participants may have already sensed that reductions in cooking-related pollution will have minimal health impacts in the presence of the high levels of ambient pollution they experience every day. Furthermore, respondents who believe that the stove will have larger health impacts on average do not have higher WTP, unlike beliefs about financial savings which are strongly correlated with WTP. 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).

4.4 Physiological mechanisms: Relating pollution and health

As discussed in Section 1, air pollution spikes may have very different health impacts than the mean daily levels that were investigated in much of the literature studying ambient

randomized, it is unlikely that this biased the results in any meaningful way.

air pollution. The significant reduction in intense, short-term spikes likely contributed to the reduction of self-reported—and largely transient rather than chronic—respiratory 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 with reduced spikes in air pollution.

The evidence above is therefore consistent with a model where short-term spikes drive short-term symptoms, whereas clinical health impacts are driven primarily by long-term ambient exposures. In other words, while reductions in spikes in exposure can generate important short-term health benefits, improvements in long-term measures of health may require reductions in ambient air pollution exposure. This result also has distributional implications regarding who is exposed to pollution: in addition to being less able to afford improved private technologies, respondents with lower wealth also on average face higher levels of ambient air pollution (Table B33).

Table 6 shows correlations between health and three key moments of pollution: average pollution exposure (in 100 $\mu g/m^3$), pollution exposure spikes (defined as the highest hourly average recorded, in 100 $\mu g/m^3$), and the duration of high pollution (above in 100 $\mu g/m^3$) exposure (Table B20 shows more detailed outcomes, and specifications that control for average pollution). Hourly pollution spikes are strongly correlated with self-reported health symptoms, but not with any of the clinical health outcomes. That mean and median PM2.5 air pollution are not correlated with health is likely due to an absence in sufficient identifying variation in ambient exposure, rather than an absence of a relationship between aggregate pollution exposure and health.

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 B21). 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 B22).

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 im-

Table 6: Correlations with different moments of the PM2.5 distribution

	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 index (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 visit 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. Table B20 shows additional variables. Table B14, Table B15, and Table B13 present detailed results on symptoms and diagnoses.

provements. 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 B23). We refrain from over-interpreting this result because the rural sample is very small ($n = 53$) and because moving is an endogenous choice that may bias the estimation.

4.5 Impacts of stove ownership on socio-economic outcomes

Panel B of Table 2 presents the impact of stove adoption on various socioeconomic outcomes (Table B5 presents a more detailed version). Improved cookstove ownership causes a \$1.50 reduction in average weekly charcoal expenditures, or a 41% reduction relative to the control group. These savings correspond to 9.3% of the control group's average income: in other words, adoption saves more than one month of income per year. These numbers correspond closely to the estimates from Berkouwer and Dean (2022a). The USD conversion (approximately \$86 per year) is slightly lower due to Kenya's high inflation in recent years.

Importantly, the large financial savings could be a mechanism through which stove adoption improves health. For example, adopters could use the savings to improve the quality or quantity of the food they consume, purchase medical defense technologies such as insecticide-treated bednets or vaccinations, or afford medications and doctors' visits. Conversely, increases in hospital visits could cause us to underestimate the impact of pollution on health if they change the conditional likelihood of being diagnosed or informed of a disease by a medical professional. Still, several factors suggest the income effect is likely to be small in this context, with the health impacts more likely to be driven by the reduction in pollution spikes per se. First, we see no change in the propensity of the respondent to purchase protein-rich foods such as meat, fish, or egg (Table B7). The propensity to cook Githeri increases, but Githeri contains only beans and maize, which more than 90% of participants were already consuming at baseline. Second, we see no change in healthcare utilization, which includes hospital visits, hospital expenditures, and non-hospital health expenditures (Table B17).

Third, the reduction in self-reported symptoms is driven by respiratory symptoms, while we see almost no reductions in non-respiratory symptoms. One exception to this is a suggestive (statistically significant at the 10% level) decrease in the occurrence of malaria. We interpret this cautiously given that we see increases in other non-respiratory health outcomes—such as worms and 'other accidents'—and the result on malaria could be due to statistical noise and the number of outcomes that we inquire about. If the reduction in malaria rates is real, this likely has important quality-of-life benefits, however it is unlikely to explain the reduction in respiratory symptoms that we see.

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. We see no impacts on savings or formal banking access, suggesting the financial savings may have been spent on consumption. We see no impacts on hours worked or earnings. Finally, we see no impact on time spent on various activities such as sleeping, working, eating, or walking (Table B24).

4.6 Self-reports and experimenter demand

The difference in results between the self-reported respiratory symptoms and the clinical health outcomes could be caused by bias from self-reports. Existing research in the medical literature has documented some degree of discrepancy between patient self-reports and medical records.[28] In this section we explore the extent to which this may drive our results.

[28] See for example Skinner et al. (2005), Katz et al. (1996), Akker et al. (2014), and Fowles, Fowler, and Craft (1998). Tisnado et al. (2006) explore how concordance varies by patient characteristics.

A critical concern when using self-reported data is that self-reports may be driven by experimenter demand. Subsidies in the study ranged from 25%–90%, and participants who received a 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 B25). Second, there are correlations between self-reported non-respiratory symptoms and blood pressure as well as between self-reported health diagnoses and blood pressure, suggesting these self-reports carry a meaningful signal (Table B19). Third, the relationship between self-reported health symptoms and objectively measured pollution spikes provides credence to the self-reports (Table 6). Finally, 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.

One other 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 smoke exposure spikes. Because the intensity of the spikes 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.

4.7 Attrition

702 of the 942 respondents (75%) were surveyed successfully during the three-year follow-up survey.[29] Attrition is not correlated with their randomly assigned BDM price, credit treatment assignment, initial Jikokoa stove adoption, or baseline health outcomes (Table B27). Attrition is slightly higher among respondents with fewer children, fewer household mem-

[29] 13 of the 955 respondents who had completed the main visit in 2019 had withdrawn from the study between 2019 and 2022.

bers, and younger respondents (such respondents may more easily move around, making them harder to track).

As a rule we attempted to survey any respondent still residing in Kenya. 167 respondents could not be contacted by phone. Physical attempts to track individuals were hampered by the recent demolitions of housing in Nairobi's settlement areas (The Star, 2023).

The remaining 73 respondents who were contacted but who chose not to complete the 2022-2023 survey made this choice for a variety of reasons, including nonavailability, non-consent, outmigration, or physical incapacitation (Table B28). Seven study participants had deceased.

5 Conclusion

Air pollution is a significant contributor to global morbidity and mortality. Extensive research documents a negative causal relationship between daily average air pollution and health. Yet, despite active regulatory and policy debate, there is scant evidence about the impacts of persistent transient spikes in air pollution and whether reducing these spikes can generate meaningful health improvements. This question is crucial in addressing pollution from, for example, commuting and cooking, two near universal sources of air pollution. However, the topic has been difficult to answer because economic activity, human behavior, and demographic patterns can all increase the wedge between pollution recorded by stationary monitors (which includes most regulatory monitors) and realized individual-level pollution exposure (the policy-relevant object for understanding health impacts).

To fill this gap, we conduct a field 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 that persists even more than three years later. We find that improved stove ownership causes a 42% reduction in air pollution spikes generated during cooking hours. As a result, respondents experience a 0.24 standard deviation improvement in self-reported respiratory symptoms.

However, we find a comprehensive lack of impacts on clinical health as measured through a range of outcomes, including blood pressure, blood oxygen, and diagnoses of chronic diseases (such as pneumonia), for both adults and children. This may be because of the lack of impacts on average pollution exposure: 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 (2%) and statistically insignificant reduction in average air pollution exposure. This can explain the

Taken together, these results are consistent with a physiological model where pollution spikes affect short-term health and daily averages affect clinical, chronic health. Given the high levels of ambient pollution experienced in many low- and middle-income country cities, this suggests that the urban poor have only limited ability to improve their health through the private adoption of improved technologies. Instead, clinical health may require government intervention addressing the negative pollution externality generating high levels of ambient pollution.

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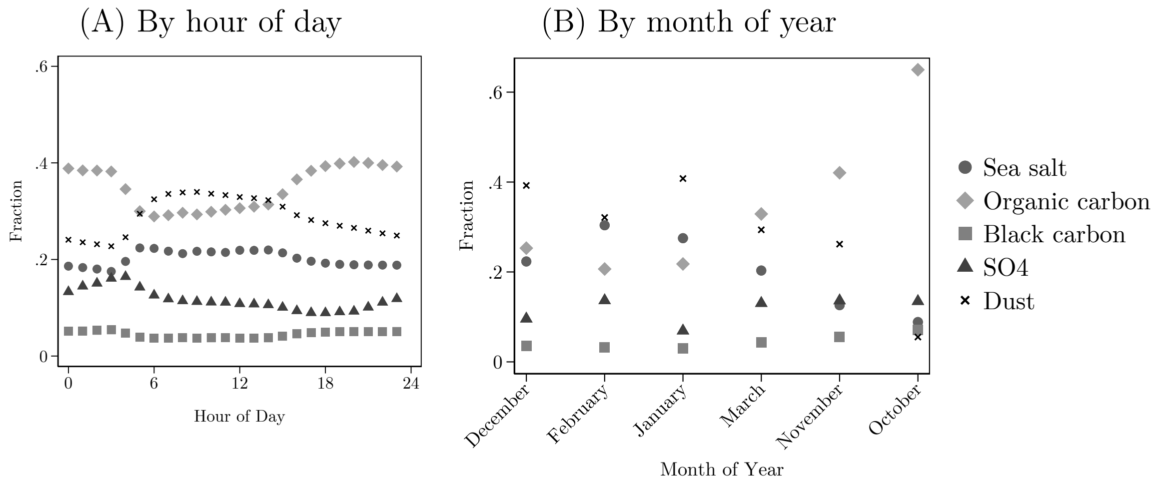
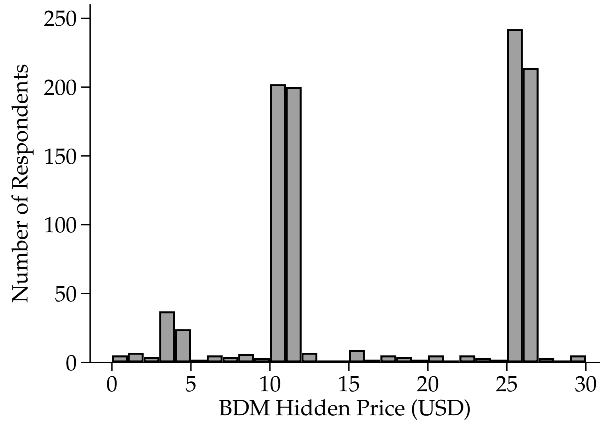
A Online Appendix Figures

Figure A1: Contents of PM2.5 in Nairobi, Kenya



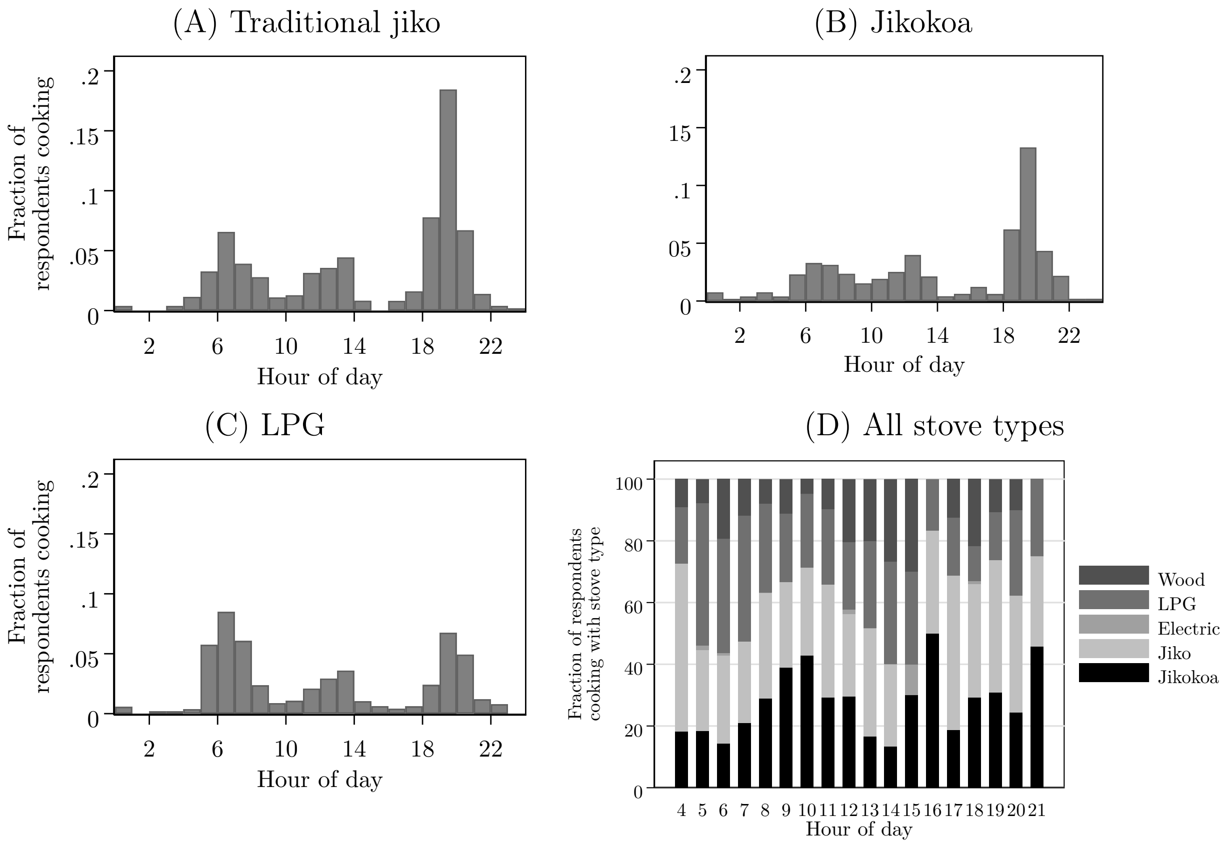
Contents of particulate matter (PM2.5) as a fraction as recorded by MERRA-2 satellites (NASA GMAO 2015; 2015).

Figure A2: BDM Hidden price distribution



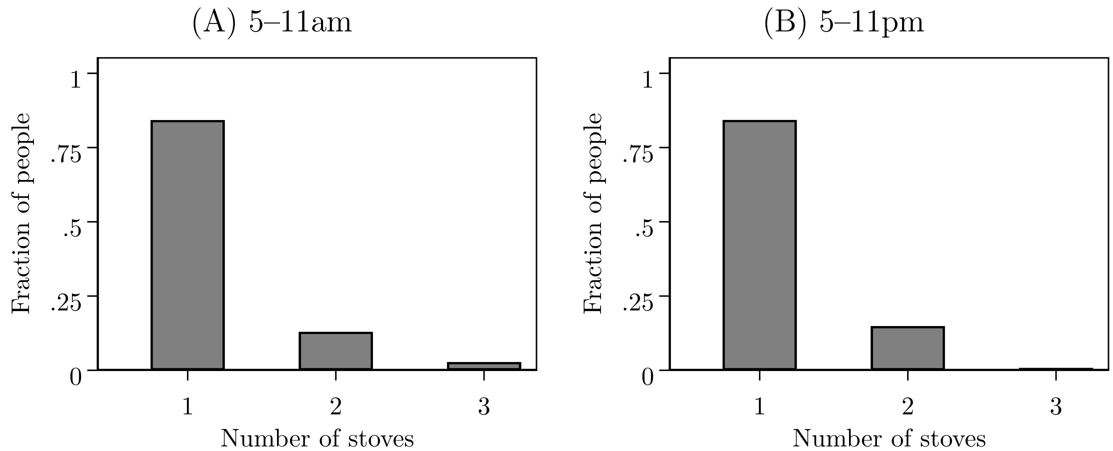
Reproduced from Berkouwer and Dean (2022a). The distribution of prices P_i used in the BDM elicitation mechanism. 6% of participants are allocated a price drawn from $U[3.50, 4.50]$, 39% of participants are allocated a price drawn from $U[10, 12]$, and 44% of participants are allocated a price drawn 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



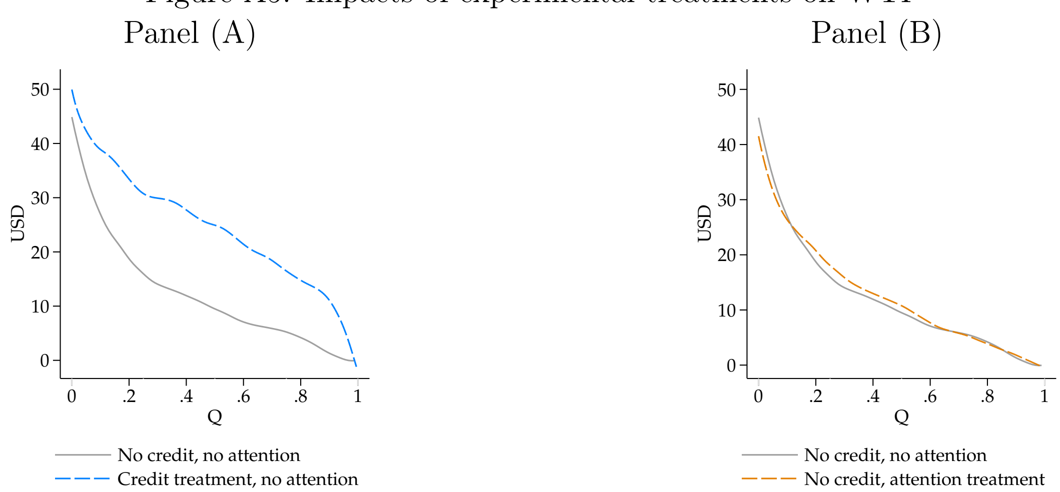
Panels (A), (B), and (C) show the fraction of respondents who report using a particular cooking technology across the various hours of the day. Panel (D) shows the same as a percentage of people who report cooking during each hour.

Figure A4: Stacking rates in morning and evening hours



The number of unique stove types used during each period, among people who report cooking at least once during each period.

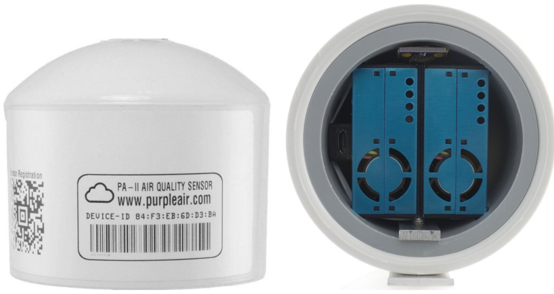
Figure A5: Impacts of experimental treatments on WTP



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 A6: Devices to record air pollution and mesh backpacks containing them

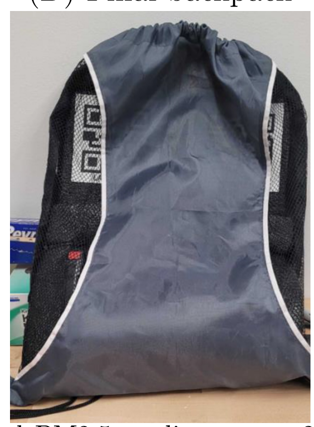
(A) Particulate Matter



(B) Carbon Monoxide

(C) Backpack contents

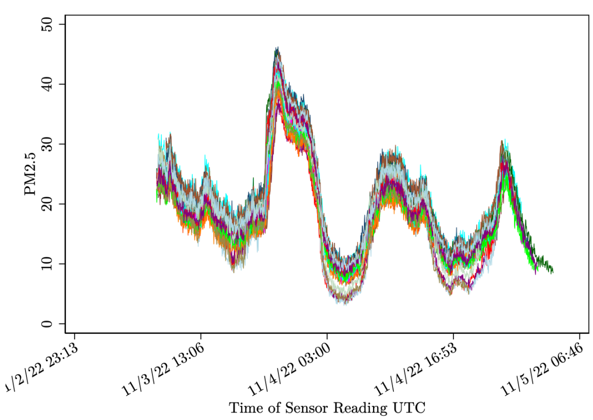
(D) Final backpack



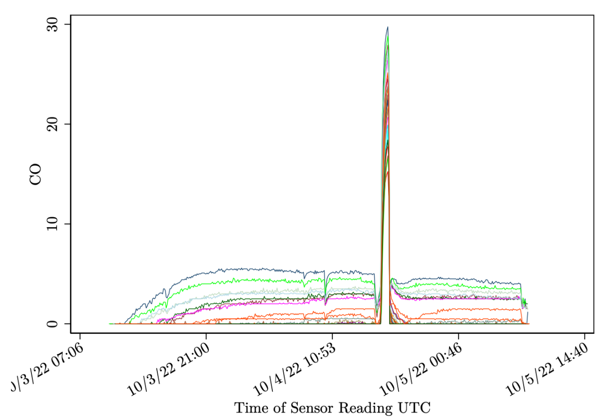
Panel A shows a Purple Air Inc. device, which records PM1.0 and PM2.5 readings every 2 minutes. Panel B shows a Lascar Electronics device, which records one CO reading every minute. Panel C displays how the devices are affixed to a lightweight foam material to stay in place. Behind the purple air device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

Figure A7: Co-located air pollution readings for devices

A) PM2.5 (PA-II devices)



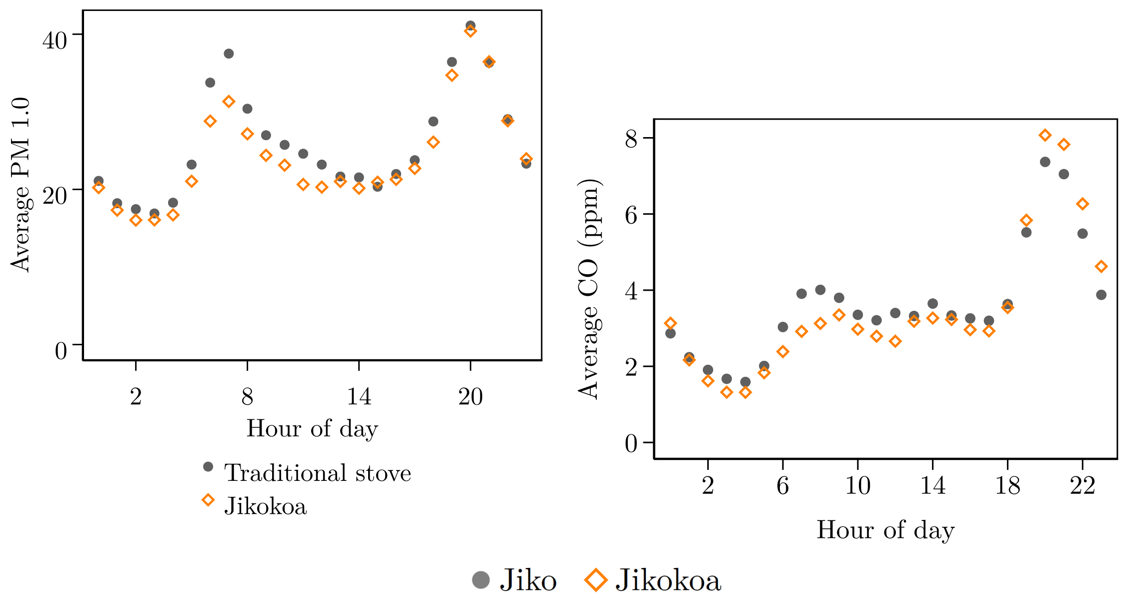
B) CO (LASCAR devices)



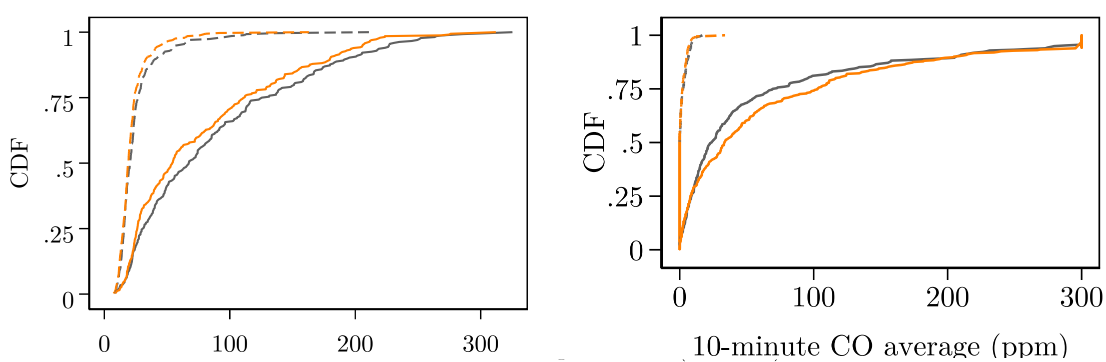
Air pollution data from a 48-hour testing window during which all 68 devices (34 PA-II devices and 34 LASCAR devices) were placed in the same location (Busara offices). To capture level differences across devices, all regressions include device fixed effects where relevant.

Figure A8: Particulate Matter (PM1.0, in $\mu g/m^3$) and Carbon Monoxide pollution by Jikokoa ownership

A) Average hourly exposure over the hours of the day

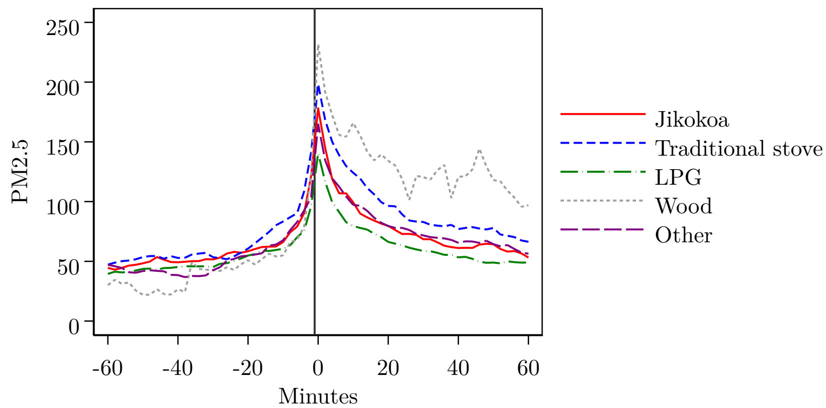


B) Distribution of 10th and 50th percentile of 10-minute concentrations, across individuals



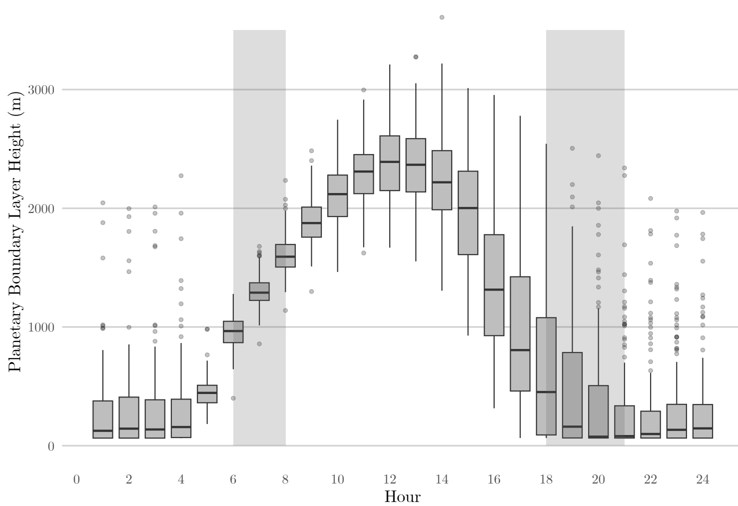
Panel A presents average PM1.0 and CO exposure by hour of day and endline Jikokoa ownership, as collected by respondents wearing backpacks for on average 48 hours. Panel B presents the distribution of mean and 99th percentile 10-minute average exposure across respondents. Figure 5 presents the same for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

Figure A9: Diffusion of PM2.5 after reaching peak while cooking



Each line represents the mean PM2.5 for the 60 minutes before and after an individual reaches their peak pollution while cooking with a particular stove. In instances where an individual's peak pollution was reached when they reported cooking with multiple stoves simultaneously, we attributed that peak to the stove that on average pollutes more. "Traditional stove" refers a charcoal-burning cookstove that is not a Jikokoa.

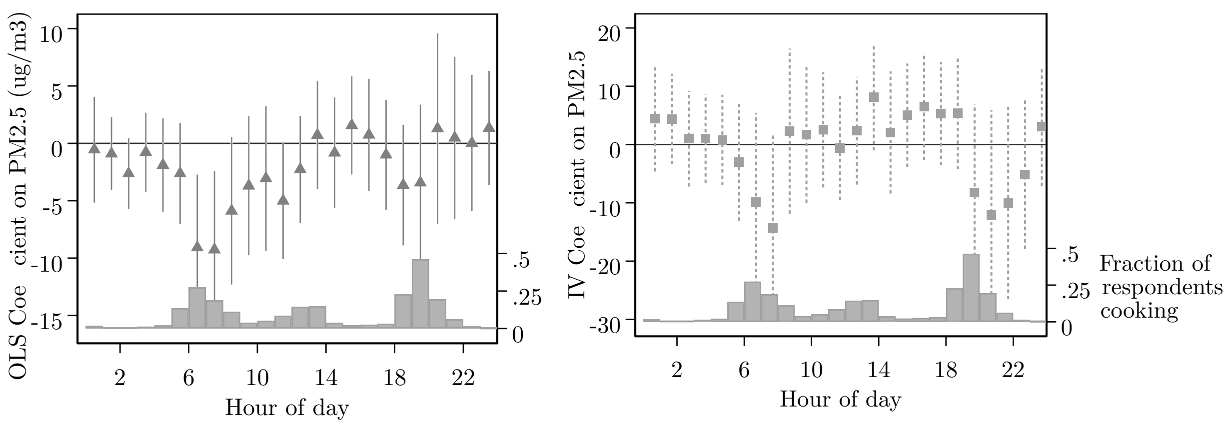
Figure A10: Planetary boundary layer height using MERRA-2 satellite data



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.

Figure A11: Correlation between Jikokoa ownership and average hourly PM2.5 (in $\mu g/m^3$)

(A) OLS Coefficients (B) IV Coefficients



Coefficients from an OLS regression of PM2.5 on Jikokoa ownership. 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. Figure 6 presents the Instrumental Variables version.

B Online Appendix Tables

Table B1: Experimental research on cookstove impacts

Authors	Year	Country	Urban	Pollution Monitored	Health Measure-ments	Point Estimate	House-holds
Berkouwer and Dean	2023	Kenya	Yes	PM, CO	Yes	-2%	702
RESPIRE trial papers							
McCracken *et al.*	2007	Guatemala	No	PM	Yes	-61%	537
Smith-Sivertsen *et al.*	2009	Guatemala	No	CO	Yes	-62%	534
Smith *et al.*	2011	Guatemala	No	CO	Yes	-50%	534
Thompson *et al.*	2011	Guatemala	No	CO	Yes	-39%	266
Romieu *et al.*	2009	Mexico	No	*None*	Yes	NA	668
Burwen and Levine	2012	Ghana	No	CO	No	+0.24 SD	488
Beltramo and Levine	2013	Senegal	No	PM, CO[b]	No	+24%	790
Alexander *et al.*	2014	Bolivia	No	CO	No	-79%	20
Jary *et al.*	2014	Malawi	No	PM, CO	Yes	-1.88 SD	50
Bensch and Peters	2015	Senegal	No	*None*	Yes	NA	253
Tielsch *et al.*	2016	Nepal	No	PM	No	-33%	3376
Hanna *et al.*	2016	India	No	CO	Yes	-3%	2575
Mortimer *et al.*	2017	Malawi	No	*None*	Yes	NA	8470
Alexander *et al.*	2018	Nigeria	Yes	PM, CO	No[a]	-11%	324
Checkley *et al.*	2021	Peru	No	PM, CO[b,c]	Yes	-21%	180
Adane *et al.*	2021	Ethiopia	No	PM	No	-46%	1977
Clasen *et al.*	2022	[d]	No	PM, CO[c]	Yes	-66%	3200

"Pollution Monitoring" refers to quantitative monitoring using a pollution device. "Health Measurements" refer to quantitative measurements (most commonly blood pressure, blood oxygen saturation, or spirometry). 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]Guatemala, India, Peru, and Rwanda.

Table B2: 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 B3: Correlation of Time Use and Pollution Exposure

	Mean Hours Per Day (1)	PM2.5 (2)	CO (3)
Jikokoa: Indoors (=1)	0.54	-0.01	0.36
	[1.06]	(0.93)	(0.35)
Jikokoa: Outdoors (=1)	0.08	-2.21	-0.14
	[0.38]	(2.16)	(0.81)
Traditional Stove: Indoors (=1)	0.64	0.61	0.10
	[1.31]	(0.74)	(0.28)
Traditional Stove: Outdoors (=1)	0.18	1.56	0.22
	[0.96]	(0.95)	(0.35)
LPG: Indoors (=1)	0.59	-0.64	-0.64*
	[0.99]	(0.96)	(0.36)
LPG: Outdoors (=1)	0.00	-2.74	1.63
	[0.04]	(19.46)	(7.27)
Wood Fire: Indoors (=1)	0.09	1.33	-0.63
	[0.51]	(2.15)	(0.80)
Wood Fire: Outdoors (=1)	0.04	4.89***	0.62
	[0.49]	(1.80)	(0.67)
Electric: Indoors (=1)	0.02	2.86	-1.90
	[0.16]	(5.09)	(1.90)
Other stove: Indoors (=1)	0.27	-0.16	0.37
	[0.71]	(1.29)	(0.48)
Eating away from home	1.91	0.02	0.16
	[0.93]	(1.13)	(0.42)
Eating at home	0.55	1.58	0.07
	[0.93]	(1.04)	(0.39)
On Bus	0.38	-1.53*	-0.51*
	[1.11]	(0.82)	(0.31)
On Bike	0.03	0.64	0.85
	[0.19]	(4.45)	(1.66)
Walking	1.93	0.49	0.03
	[2.32]	(0.41)	(0.15)
At work: Indoors	2.22	0.60*	0.09
	[3.81]	(0.34)	(0.13)
At work: Outdoors	2.96	0.43	0.13
	[4.05]	(0.32)	(0.12)
Doing Schoolwork: Outdoors	0.01	1.14	-0.48
	[0.20]	(4.59)	(1.72)
Doing Schoolwork: Indoors	0.07	-3.65	-0.42
	[0.34]	(2.83)	(1.06)
Other activities: Away	0.84	0.78	0.22
	[1.63]	(0.62)	(0.23)
Other activities: Home	3.99	0.24	0.34**
	[3.56]	(0.38)	(0.14)
Sleeping	6.09	30.41	3.93
	[2.74]	[33.21]	[11.88]
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. Controls include socioeconomic controls, PA-II or Lascar device fixed effects, and field officer fixed effects. Hour spent sleeping was omitted from the regressions. The mean hours per day spent sleeping, PM2.5 levels while, and CO levels while sleeping are presented in the penultimate row. No one in our sample used an electric stove or "other" stove outdoors.

Table B4: 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 (USD 10-40), credit treatment status, and their interaction on endline Jikokoa ownership, estimated using OLS.

Table B5: 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 B6: Causal impact of cookstove adoption on cooking behavior

	Minutes per day	Cooking (=1)		Cooking indoors (=1)	
	(1)	(2)	(3)	(4)	(5)
Own Jikokoa	4.131	0.013	0.014	-0.026	-0.065
	(9.025)	(0.010)	(0.010)	(0.047)	(0.061)
Control Mean	137.013	0.101	0.101	0.889	0.872
HOD FE	N/A	N/A	Yes	N/A	Yes
Weak IV F-Stat	51	51	69	46	47
Observations	697	697	31887	649	3068

Instrumental variables regressions using randomly assigned price and credit treatment status as instruments for endline Jikokoa ownership. Column (1) uses survey data. Columns (3) and (5) use hourly time use data. Columns (2) and (4) use time use data averaged at the household level. Columns (4) and (5) are conditional on cooking in that hour. Regression includes socioeconomic controls.

Table B7: 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 B8: Causal impact of cookstove adoption on CO exposure

Panel A) All hours

	PM2.5			
	(1)	(2)	(3)	(4)
	Median	Mean	Max Hour	99th
Own Jikokoa	-0.5	2.2	21.5*	25.6*
	(0.4)	(1.7)	(12.8)	(15.1)
Control Mean	1.8	6.5	49.6	61.6
Weak IV F-Statistic	52	52	52	52
Observations	656	656	656	656

Panel B) When self-reporting cooking

	PM2.5			
	(1)	(2)	(3)	(4)
	Median	Mean	Max Hour	99th
Own Jikokoa	1.1	1.4	8.3	6.2
	(2.1)	(3.1)	(9.9)	(14.2)
Control Mean	4.2	9.2	25.3	41.3
Weak IV F-Statistic	47	47	47	47
Observations	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. Column (1) uses median exposure, (2) uses mean exposure, (3) uses maximum 1-hour average exposure, and (4) uses 99th percentile of 10-min average exposure. Of the 702 respondents surveyed, 656 consented to having at least one air pollution monitoring device (Section 4.7 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 3 presents the same for PM2.5. Table B9 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 B10 presents all four outcomes in logs.

Table B9: 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) Median	(2) Mean	(3) Max Hour	(4) 99th	(5) Median	(6) Mean	(7) Max Hour	(8) 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) Median	(2) Mean	(3) Max Hour	(4) 99th	(5) Median	(6) Mean	(7) Max Hour	(8) 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

IV with randomly assigned price, credit treatment status, and their interaction 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 LASCAR or PA-II device FE. Table 3 presents the same for all hours and for when self-reporting cooking. Table B10 presents all four outcomes in logs.

Table B10: 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 3 presents the same for all hours and for when self-reporting cooking.

Table B11: 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 B12: 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 B13: 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 B14: 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 B15: 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 B16: 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 3.5 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 B17: Healthcare utilization outcomes

	Control Mean	Treatment Effect	N
Non-hospital health expenditures (USD)	4.34	0.80	702
	[7.64]	(1.07)	
Hospital visits in past 30 days	0.33	-0.01	702
	[0.57]	(0.09)	
Hospital visit expenditures (USD)	3.39	1.03	702
	[11.17]	(1.48)	

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 B18: Children's outcomes

	Control Mean	Treatment Effect	N
Child weight (z-score)	0.57	-0.96	223
	[2.57]	(0.88)	
Child height (z-score)	-1.95	1.31	199
	[6.82]	(1.70)	
Child arm circumference (z-score)	0.60	1.76	142
	[7.05]	(1.95)	
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. Z-scores are calculated using data from WHO (2006) and Onis et al. (2007), which combined provides mean and standard deviation heights for children age 0 to 19. We subtract each child's height with the mean for children of their age, then divide by the associated standard deviation to create the z-scores. The WHO only provides data on arm circumference for children age 5 or younger, so we do not include children older than five in that regression. '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 B19: Correlation of blood pressure and blood oxygen with self-reported health outcomes

	Mean (1)	Blood Pressure (2)	Blood Oxygen (3)	N (4)
Health symptoms index (z-score)	-0.00	0.03	-0.01	696
	[1.00]	(0.04)	(0.04)	
Number of health symptoms	2.47	0.05	-0.02	696
	[2.64]	(0.10)	(0.10)	
Respiratory health symptom index	-0.00	-0.03	-0.01	696
	[1.00]	(0.04)	(0.04)	
Number of respiratory health symptoms	1.53	-0.04	0.00	696
	[1.59]	(0.06)	(0.06)	
Non-respiratory health symptom index	0.00	0.07*	-0.01	696
	[1.00]	(0.04)	(0.04)	
Number of non-respiratory health symptoms	0.94	0.09	-0.02	696
	[1.42]	(0.06)	(0.05)	
Health diagnoses index	-0.00	0.11***	0.03	696
	[1.00]	(0.04)	(0.04)	
Number of health diagnoses	0.28	0.06***	0.02	696
	[0.55]	(0.02)	(0.02)	
Cognitive index	0.06	0.01	0.03	581
	[1.03]	(0.04)	(0.04)	
Hospital visits in past 30 days	0.28	-0.01	0.01	696
	[0.53]	(0.02)	(0.02)	
Hospital visit expenditures (USD)	2.75	0.24	0.34	696
	[10.14]	(0.43)	(0.42)	

Each cell in columns (2) and (3) is an OLS regression of the row variable on standard deviations of either blood pressure or blood oxygen. Column (1) presents the mean of the row variable over the entire sample. Regressions include socioeconomic controls. Table B30, Table B31, and Table B32 provide correlations of blood pressure and blood oxygen with more detailed outcomes on diagnoses, respiratory symptoms, and non-respiratory symptoms respectively.

Table B20: 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 (>140/90)	0.27	0.00	-0.01	-0.01	0.00	0.00	645
	[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 symptoms	0.96	0.03	0.15***	0.15***	0.02	0.02	651
	[1.44]	(0.06)	(0.06)	(0.06)	(0.03)	(0.03)	
Non-respiratory health symptom index	-0.07	0.02	0.09**	0.09**	0.01	0.01	651
	[0.99]	(0.04)	(0.04)	(0.04)	(0.02)	(0.02)	
Number of respiratory health symptoms	1.55	-0.01	0.08	0.08	0.00	0.00	651
	[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 days	0.30	-0.01	0.01	0.01	-0.00	-0.00	651
	[0.55]	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	
Non-hospital health expenditures (USD)	4.17	0.63*	0.60*	0.60*	0.28	0.28	651
	[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 B14, Table B15 and Table B13 present detailed results on symptoms and diagnoses.

Table B21: 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 B22: Primary health outcomes by ambient concentrations

	Treatment (1)	Treatment X Ambient (2)	N
Average systolic blood pressure	-1.09	3.38	649
	(4.71)	(5.99)	
Average diastolic blood pressure	1.54	-1.29	649
	(2.87)	(4.03)	
Hypertension: Stage 1 or higher (>130/80)	0.07	-0.13	649
	(0.11)	(0.17)	
Hypertension: Stage 2 or higher (>140/90)	-0.02	0.05	649
	(0.10)	(0.15)	
Blood oxygen	-0.07	0.41	649
	(0.41)	(0.67)	
Number of non-respiratory health symptoms	0.11	-0.74	655
	(0.31)	(0.52)	
Non-respiratory health symptom index	0.07	-0.23	655
	(0.22)	(0.38)	
Number of respiratory health symptoms	-0.33	-0.15	655
	(0.28)	(0.45)	
Respiratory health symptom index	-0.16	-0.06	655
	(0.17)	(0.25)	
Health diagnoses index	0.03	0.15	655
	(0.24)	(0.31)	
Number of health diagnoses	0.08	0.10	655
	(0.13)	(0.19)	
Cognitive index	-0.18	0.26	547
	(0.22)	(0.30)	
Non-hospital health expenditures (USD)	1.14	0.03	655
	(1.43)	(2.31)	
Hospital visits in past 30 days	-0.02	0.02	655
	(0.13)	(0.19)	
Hospital visit expenditures (USD)	1.06	2.22	655
	(1.68)	(3.05)	
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 B23: Primary health outcomes for rural respondents

	Control Mean (1)	Treatment Effect (2022 Ownership) (2)	Treatment Effect (2019 ownership) (3)	N
Physiological 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 4 presents results for the full sample.

Table B24: 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 B25: 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 B26: Correlation between health and mean, median, maximum, and duration of PM2.5 exposure (among 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)	0.50	0.02	0.01	0.01	0.01	355
	[0.50]	(0.03)	(0.04)	(0.03)	(0.02)	
Blood oxygen	96.84	-0.15	0.03	-0.31**	-0.15*	355
	[2.30]	(0.15)	(0.17)	(0.12)	(0.08)	
Health symptoms index (z-score)	-0.18	0.00	-0.03	0.05	0.01	360
	[0.83]	(0.05)	(0.05)	(0.04)	(0.03)	
Number of health symptoms	2.27	-0.00	-0.06	0.14	0.02	360
	[2.38]	(0.14)	(0.15)	(0.12)	(0.08)	
Health diagnoses index	-0.09	-0.04	0.04	-0.02	-0.03	360
	[0.79]	(0.05)	(0.06)	(0.05)	(0.03)	
Number of health diagnoses	0.28	-0.04	-0.00	-0.03	-0.02	360
	[0.54]	(0.04)	(0.04)	(0.03)	(0.02)	
Hospital visits in past 30 days	0.26	-0.02	-0.02	0.00	0.01	360
	[0.51]	(0.03)	(0.04)	(0.03)	(0.02)	
Hospital visit expenditures (USD)	2.34	0.11	0.03	0.06	0.09	360
	[9.43]	(0.64)	(0.69)	(0.56)	(0.35)	

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 6 present the same for the entire sample.

Table B27: 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 B28: 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 B29: 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 B14, Table B15 and Table B13 present detailed results on symptoms and diagnoses.

Table B30: Correlation of blood pressure and blood oxygen with self-reported respiratory diagnoses

	Mean (1)	Blood Pressure (2)	Blood Oxygen (3)	N (4)
Asthma	0.00	0.00	0.00	696
	[0.05]	(0.00)	(0.00)	
Pneumonia	0.12	0.01	0.01	696
	[0.32]	(0.01)	(0.01)	
Chronic Pulmonary Disease	0.00	0.00	-0.00	696
	[0.04]	(0.00)	(0.00)	
Other lung disease	0.00	0.00	0.00	696
	[0.07]	(0.00)	(0.00)	
Stroke or cardiovascular disease	0.00	0.00	-0.00	696
	[0.05]	(0.00)	(0.00)	
Hypertension	0.06	0.06***	0.01	696
	[0.23]	(0.01)	(0.01)	
Tuberculosis	0.00	-0.00	0.00	696
	[0.05]	(0.00)	(0.00)	
COVID	0.01	0.00	0.00	696
	[0.08]	(0.00)	(0.00)	
Diabetes	0.02	0.00	0.00	696
	[0.14]	(0.01)	(0.01)	
Other	0.04	-0.01	0.00	696
	[0.19]	(0.01)	(0.01)	
Typhoid	0.02	-0.01	-0.00	696
	[0.13]	(0.01)	(0.01)	
Tuberculosis	0.00	0.01***	-0.00	696
	[0.07]	(0.00)	(0.00)	
Cholera	0.00	0.00	-0.00	696
	[0.05]	(0.00)	(0.00)	

Each cell in columns (2) and (3) is an OLS regression of the row variable on standard deviations of either blood pressure or blood oxygen. Column (1) presents the mean of the row variable over the entire sample. Regressions include socioeconomic controls.

Table B31: Correlation of blood pressure and blood oxygen with self-reported respiratory symptoms

	Mean (1)	Blood Pressure (2)	Blood Oxygen (3)	N (4)
Respiratory health symptom index	-0.00	-0.03	-0.01	696
	[1.00]	(0.04)	(0.04)	
Number of respiratory health symptoms	1.53	-0.04	0.00	696
	[1.59]	(0.06)	(0.06)	
Persistent cough	0.23	-0.00	0.01	696
	[0.42]	(0.02)	(0.02)	
Always feeling tired	0.28	0.01	0.02	696
	[0.45]	(0.02)	(0.02)	
Breathlessness at night	0.06	-0.00	-0.00	696
	[0.25]	(0.01)	(0.01)	
Frequent diarrhea	0.02	-0.00	0.00	696
	[0.12]	(0.01)	(0.00)	
Difficulty breathing / Chest tightness	0.06	-0.02*	-0.01	696
	[0.23]	(0.01)	(0.01)	
Runny nose	0.22	-0.01	-0.01	696
	[0.41]	(0.02)	(0.02)	
Sore throat	0.15	-0.00	0.00	696
	[0.36]	(0.01)	(0.01)	
Headache	0.48	-0.00	0.00	696
	[0.50]	(0.02)	(0.02)	
Wheezing	0.03	-0.00	-0.01	696
	[0.16]	(0.01)	(0.01)	
Persistent mucus problems	0.02	-0.01	0.00	696
	[0.15]	(0.01)	(0.01)	

Each cell in columns (2) and (3) is an OLS regression of the row variable on standard deviations of either blood pressure or blood oxygen. Column (1) presents the mean of the row variable over the entire sample. Regressions include socioeconomic controls.

Table B32: Correlation of blood pressure and blood oxygen with self-reported non-respiratory symptoms

	Mean (1)	Blood Pressure (2)	Blood Oxygen (3)	N (4)
Non-respiratory health symptom index	0.00	0.07*	-0.01	696
	[1.00]	(0.04)	(0.04)	
Number of non-respiratory health symptoms	0.94	0.09	-0.02	696
	[1.42]	(0.06)	(0.05)	
Fever	0.22	0.04**	-0.00	696
	[0.42]	(0.02)	(0.02)	
Malaria	0.13	-0.01	-0.02	696
	[0.33]	(0.01)	(0.01)	
Stomach pain	0.13	0.01	0.01	696
	[0.33]	(0.01)	(0.01)	
Pain when urinating	0.01	0.00	-0.00	696
	[0.11]	(0.00)	(0.00)	
Worms	0.01	0.00	0.00	696
	[0.11]	(0.00)	(0.00)	
Rapid weight loss	0.05	-0.01	0.00	696
	[0.21]	(0.01)	(0.01)	
Frequent and excessive urination	0.02	0.02**	-0.00	696
	[0.15]	(0.01)	(0.01)	
Skin Rash or irritaion	0.02	0.00	-0.00	696
	[0.13]	(0.01)	(0.01)	
Constant thirst / increased drinking of fluids	0.13	-0.00	-0.01	696
	[0.33]	(0.01)	(0.01)	
Difficulty swallowing	0.02	0.00	0.01	696
	[0.14]	(0.01)	(0.01)	
Muscle pain (myalgia)	0.09	0.02	-0.00	696
	[0.29]	(0.01)	(0.01)	
Loss of sense of smell / not being able to taste food	0.03	-0.00	-0.00	696
	[0.17]	(0.01)	(0.01)	
Diarrhea / Nausea / Vomiting	0.03	0.01	0.01	696
	[0.17]	(0.01)	(0.01)	
Swelling in ankles, feets or legs	0.03	0.01	0.00	696
	[0.18]	(0.01)	(0.01)	
Other accidents	0.02	0.00	-0.01	696
	[0.14]	(0.01)	(0.01)	

Each cell in columns (2) and (3) is an OLS regression of the row variable on standard deviations of either blood pressure or blood oxygen. Column (1) presents the mean of the row variable over the entire sample. Regressions include socioeconomic controls.

Table B33: Correlation of average ambient PM2.5 exposure with baseline socio-economic characteristics

	Mean	Owns Jikokoa (=1)	Mean Pollution in SD	Median Pollution in SD	Max Hourly Pollution in SD	Hours Above $100 \mu g/m^3$
	(1)	(2)	(3)	(4)	(5)	(6)
Owns Jikokoa (=1)			-0.11	-0.08	-0.06	-0.14
			(0.08)	(0.08)	(0.08)	(0.14)
Income (1 USD)	3.37	-0.00	0.00	0.01	0.00	0.00
	[3.18]	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Savings (100 USD)	0.71	0.04**	-0.08**	-0.08**	-0.05	-0.09
	[1.19]	(0.02)	(0.04)	(0.04)	(0.04)	(0.06)
Primary education (=1)	0.69	0.01	-0.06	-0.12	0.10	0.04
	[0.46]	(0.05)	(0.10)	(0.10)	(0.10)	(0.17)
Residents	4.83	0.02**	0.00	0.02	0.02	0.02
	[2.06]	(0.01)	(0.02)	(0.02)	(0.02)	(0.04)
Observations	647	647	646	647	647	647

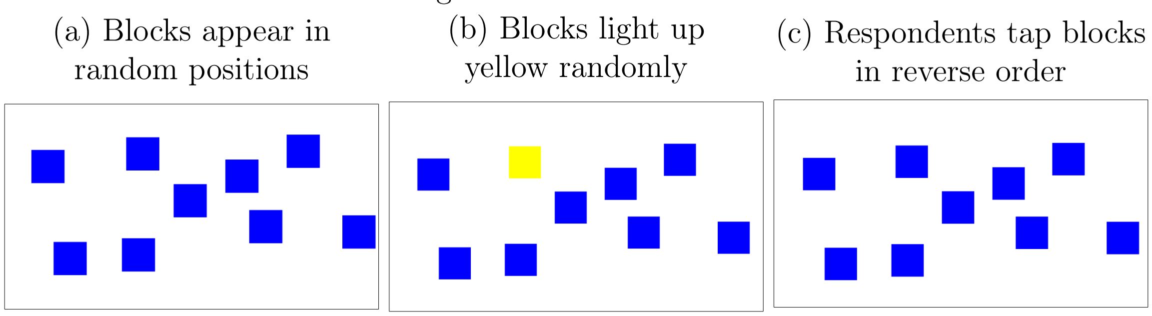
Ambient pollution only includes observations recorded during hours where the respondent did not self-report cooking. Each column is regression. Regressions control flexibly for month of survey, age, and device, and include binary indicators for female and rural.

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 B1). 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 B1: Corsi Stimuli



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 B2).

(a) Press 'Q' Key (b) Press 'P' Key

(c) Press 'Q' key (d) Press 'P' key

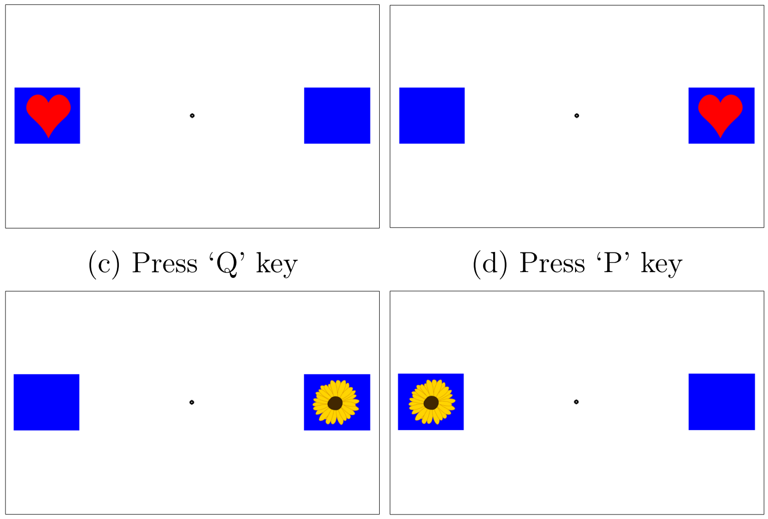


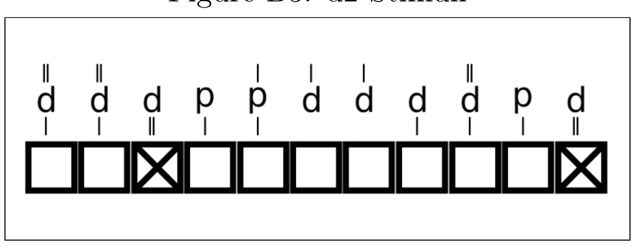
Figure B2: Hearts and Flowers Possible Stimuli and Responses

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 Brickenkamp and Zillmer (1998) and Bates and Lemay Jr. (2004). 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 B3). 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 B3: 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.