Pollution exposure and health: The role of private actions and environmental externalities in Nairobi

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Abstract

Air pollution causes around 8 million deaths each year. Many of the world's urban poor are exposed to both indoor air pollution—generated by their own use of biomass for cooking—and ambient air pollution—generated by transportation, industry, and other economic activity—yet these two major sources of pollution have thus far been studied almost entirely independently. Private actions could lower indoor air pollution, but if high ambient air pollution dampens the health benefits from private technology adoption, then meaningful health improvements will require government intervention addressing negative externalities through environmental regulation. We conduct a field experiment studying the impacts of three years of improved cookstove usage on 700 biomass cookstove users in Nairobi, Kenya. We collect detailed personal, high-frequency particulate matter (PM) and carbon monoxide (CO) concentrations and extensive quantitative and self-reported health measurements. 10-minute peak PM2.5 exposure increases by 122 $\mu g/m^3$ during cooking for the control group, but improved stove ownership reduces this by 49 $\mu g/m^3$ (40%). In line with this, we see a 0.24 standard deviation reduction in self-reported respiratory health symptoms and USD 1.65 (44%) in weekly energy savings. However, these peak pollution reductions have negligible impacts on average air pollution exposure, which are overshadowed by average ambient pollution of 36 $\mu g/m^3$. We can rule out meaningful improvements in blood pressure, blood oxygen, and a wide array of self-reported diagnoses. In the presence of high ambient pollution, private fuel switching may not generate large improvements in aggregate pollution exposure or chronic health.

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1 Introduction

According to the World Health Organization (2021) air pollution is "the single biggest environmental threat to human health." The Global Burden of Disease study (Lancet, 2017) estimates that it is responsible for 7–9 million premature deaths annually (10-15% of all deaths). However, the existing literature estimating the health impacts from air pollution contains three key shortcomings. First, existing research on ambient air pollution almost exclusively evaluates mean daily exposure (for example, Clay, Lewis, and Severnini, 2022; Deryugina et al., 2019; Graff Zivin and Neidell, 2012; Greenstone and Hanna, 2014; Isen, Rossin-Slater, and Walker, 2017; Schlenker and Walker, 2015). The limited research about how short-term exposure affects health creates uncertainty in optimal targeting of costly environmental regulations, for example, regulating peak hours versus annual averages. Second, most causal studies on improved cookstoves—a key source of pollution for the 4 billion people lacking access to modern stoves (World Bank, 2020)—are limited to short-term outcomes, lack pollution measurements, or rely on self-reported health measures (the RESPIRE trial in rural Guatemala (Smith et al., 2011) being an important exception). Third, and perhaps most importantly, there is almost no evidence evaluating pollution exposure in contexts with both high cooking and high ambient pollution, even though the 1 billion urban poor who live in slums are simultaneously chronically exposed to both: more than 90% of pollution-related deaths occur in low- and middle-income countries. This distinction has important policy implications: cookstove-generated pollution requires removing private barriers to adoption, while ambient pollution requires regulation of environmental externalities.

We conduct a randomized field study with 700 households in Kenya to estimate the impact of improved cookstoves on pollution and health in an urban context three and a half years after adoption. We randomize credit and subsidies for cookstoves to enable causal inference and conduct follow-up surveys after 3.5 years of daily use. To measure individual pollution exposure, each respondent wears a backpack containing two devices that record particulate matter under 1.0 or $2.5\mu m$ in diameter (PM1.0 and PM2.5, respectively) and parts-per-million of carbon monoxide (CO ppm) on a minute-by-minute basis for 48 hours. High-frequency monitoring allows us to separately identify impacts on mean and peak pollution exposure. A complementary time use survey records each respondent's indoor or outdoor activity during each of those 48 hours. To measure health, we complement detailed self-reports on health symptoms and diagnoses for adults and children with measurements of blood pressure, pulse oximetry, and anthropometrics. We use cognitive exercises to measure attention, working memory, and response inhibition, and a socio-economic survey to measure behavioral and financial impacts.

The analyses generate three key findings. First, the impact of the adoption subsidies persists: 3.5 years later, 83% of respondents who purchased a Jikokoa still own one while only 10% of those that did not have purchased one in the meantime. Improved cookstove users in urban areas continue to save USD 86 per year in charcoal spending, 44% of the control group (similar to Berkouwer and Dean, 2022a). In addition to providing a strong first stage with which to study the health impacts, the adoption gap demonstrates that the subsidies were marginal on the decision to adopt the stove. We also do not find evidence of crowd out of the adoption of other cleaner cooking technologies. Combining the results on persistence with the impacts on emissions from Berkouwer and Dean (2022a), we estimate an upper bound on the abatement cost of distributing stoves for free of around \$4 per ton of carbon dioxide equivalent (tCO_2e)—significantly lower than most alternative abatement technologies available today. Thus the stoves continue to have exceedingly high private and social benefits even before considering health impacts.

Second, the modern stove reduces peak cooking emissions by 40%. For the control group, peak emissions while cooking are 122 $\mu g/m^3$ higher than their median exposure, but modern stove ownership reduces this by 49 $\mu g/m^3$.[1] This can explain a statistically significant 0.24 standard deviation (SD) reduction in an index of self-reported respiratory symptoms such as sore throat, headache, cough, and runny nose. An analysis of the mechanisms confirms that these respiratory symptoms are correlated with peak levels and not with average concentrations.

Third, due to the transitory nature of the cooking emissions reductions, and high ambient pollution—average exposure of 36 $\mu g/m^3$ when not cooking—these large reductions in cooking pollution have negligible impacts on aggregate air pollution exposure ($\hat{\beta}$: –2.0, 95% CI: [-7.9, 3.9]). In turn, we see no impacts on an array of chronic health measurements (including blood pressure and blood oxygen), medical diagnoses (including pneumonia), or health-related expenditures. While improved stove adoption generates large reductions in cooking emissions, these changes have negligible pollution or health benefits against a backdrop of high ambient air pollution.

Billions of urban poor—living primarily in Africa and Asia—are exposed to high levels of both ambient and own-cooking related emissions on a daily basis. The lack of impact on average pollution exposure—and on measurable or chronic health outcomes—that we estimate indicate that private actions alone can generate only modest improvements in their health. Meaningful health improvements will require government regulation of the economic activities that generate the negative externality. This is especially the case in cities with the highest ambient air pollution: while average annual ambient PM2.5 concentrations are higher in Africa than in many OECD countries, they are higher still in many Asian cities.[2] This departs from some earlier research asserting own-household generated air pollution (HAP) plays a dominant role in aggregate pollution exposure (WHO, 2014; Fisher et al., 2021). It also fills a gap in the existing literature. Numerous papers evaluate the health impact of ambient air pollution (AAP) in LMICs,[3] however, few simultaneously measure HAP. Furthermore, Katoto et al. (2019) find that many of the 60 AAP studies in Sub-Saharan Africa either do not assess health effects or use limited direct measurements of air pollutants.

This paper also contributes rigorous causal evidence to the ongoing policy debate around the transition towards cleaner cooking technologies (Gill-Wiehl and Kammen, 2022). The HAP literature has associated a wide range of health problems with energy-intensive cookstove usage (Lee et al.

[1] For context, the EPA considers >35 $\mu g/m^3$ ($>$ 100 AQI) to be 'unhealthy for sensitive groups', >55 $\mu g/m^3$ ($>$ 150 AQI) 'unhealthy', and >150 $\mu g/m^3$ ($>$ 200 AQI) 'very unhealthy' (EPA, 2018).

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

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

(2020) and Thakur et al. (2018) provide reviews). However, the evidence on health improvements from improved cooking technologies is still primarily correlational rather than causal, often lacks quantitative measurements of pollution exposure and health outcomes, and often measures only short-term impacts (see Table A1 for an overview of the causal evidence). A recent meta-analysis in *The Lancet* identified 437 cookstove-related studies (Lee et al., 2020): only 6 were randomized trials; 24 measure personal pollution exposure concentrations, and most only include self-reported health outcomes. Many RCTs furthermore focus on adoption rather than on impacts,[4] though a notable exception is the large RESPIRE RCT conducted in a poor, rural community in Guatemala in 2002–2005 (Smith et al., 2011). In addition, the existing research is overwhelmingly rural: as of 2018, Thakur et al. (2018) identified no urban papers.[5]

Finally, our use of personally wearable PM and CO pollution monitoring devices to collect high-frequency, indoor and outdoor air pollution measurements advances our understanding of how short-term fluctuations in air pollution exposure over the course of the day affect health. Much of the existing AAP literature uses daily averages of pollution concentrations.[6] While numerous papers document causal links between physical and cognitive health and air pollution in experimental and quasi-experimental settings,[7] due to data limitations the relevance of these relationships for realized exposure in daily life remains unclear. Policy-makers have discretion over setting limits on, for example, average concentration over an entire year versus the highest average concentration experienced in a single hour. Improving our understanding of these relationships is therefore crucial for optimizing environmental regulations. To the extent that these have highly heterogeneous health effects, optimal policy requires identifying these separate relationships in order to set regulations that maximize the ratio of health benefits to abatement cost.

2 Background: Cookstoves and pollution among the urban poor

Traditional charcoal cookstoves produce indoor air pollution that causes millions of deaths each year (WHO, 2017; Bailis et al., 2015; Pattanayak et al., 2019). More than 4 billion people still do not have access to modern cooking methods (WB, 2020). 67–70 percent of the 12 million households in Kenya rely on biomass (wood and charcoal) as their primary household fuel (KNBS, 2019; WB, 2019). Around 42 percent of Kenyan households use a Kenyan ceramic *'jiko'* 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). All of this study's participants resided

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

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

[6]See Chay and Greenstone, 2003; Clay, Lewis, and Severnini, 2022; Currie and Walker, 2011; Deryugina et al., 2019; Graff Zivin and Neidell, 2012; Greenstone and Hanna, 2014; Isen, Rossin-Slater, and Walker, 2017; Schlenker and Walker, 2015.

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

in Nairobi at baseline, and their primary energy-using durable at baseline was a *jiko*. According to the World Bank's Kenya Country Environmental Analysis (2019), "Those who cook inside with poor ventilation have 400–600 $\mu g/m^3$ average annual concentration of PM2.5 in their household." These levels are extremely high: the WHO (2021) defines its 'healthy' threshold to be 5 $\mu g/m^3$.

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

2.1 The energy efficient Jikokoa cookstove

Figure 1 displays a *jiko* as well as the Jikokoa, an energy efficient charcoal stove produced by Burn Manufacturing ('Burn'), which has sold more than two million energy efficient cookstoves since 2014. Berkouwer and Dean (2022a) provides more detail on charcoal consumption, barriers to adoption, and access to credit among potential adopters in Nairobi.

Figure 1: 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 Jikokoa and the *jiko* is that the Jikokoa's main charcoal combustion chamber is constructed using improved insulation material and designed for optimized fuel-air mixing. It is made of a metal alloy that better withstands heat, and a layer of ceramic wool insulates the chamber to cut heat loss. To maximize the charcoal-to-heat conversion rate, parts are made to strict specifications, and components fit tightly to minimize air leakage. These features were designed and tested by laboratories in Nairobi and Berkeley. 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%. Adoption of the energy efficient stove does not require any behavioral adaptation or learning. The cooking processes are identical. Most adopters continue cooking the same types and quantities of food as before, using the same type of charcoal.

2.2 The physiological impacts of air pollution

Many of the leading papers studying AAP quantify the impact of average concentrations on mortality and morbidity use highly aggregated data. While a number of excellent papers document concavity in the dose-response function (see for example Gong et al., 2023; He, Fan, and Zhou, 2016; La Nauze and Severnini, 2021), this literature generally uses average concentrations rather than examining non-linearity in regards to within-day extremes. Pope et al. (2018) document that average PM2.5 and PM1.0 in Kenya are on average 2.8 times higher in urban roadside locations than in rural locations. This mimics much of the regulatory framework around environmental limits. The Environmental Protection Agency (EPA), for example, frequently target 365-day averages or 24-hour averages for PM2.5, rather than instantaneous peaks, which are often harder to measure.

Despite the importance of the problem, there is limited causal evidence quantifying the pollution and health impacts of improved cookstove adoption. The literature overwhelmingly evaluates correlational rather than causal links, and causal evidence often lacks rigorous quantitative measurements of air pollution exposure and health outcomes. In addition, few papers evaluate impacts more than 12 months after adoption. Table A1 presents an overview of causal evidence on the health and pollution impacts of improved cooking technologies. A review article in the Lancet (Gordon et al., 2014) discussed the "urgent need for clinical trials evaluating cleaner fuel interventions on health outcomes to underpin evidence-based policy and decision making." In a comprehensive meta-analysis of research on the health impacts of improved cookstoves, Thakur et al. (2018) write that "no studies in urban areas were identified by our search," and add that "it is therefore essential that the existing knowledge gap of the potential health impact of improved cookstoves in urban—in particular slum—areas is filled in future research." One challenge when trying to identify the health impacts of improved stoves, experienced by for example Beltramo and Levine (2013) and Hanna, Duflo, and Greenstone (2016), is lack of stove usage. Berkouwer and Dean (2022a) rule this out in this paper's study context.

2.3 Health measurement methodology

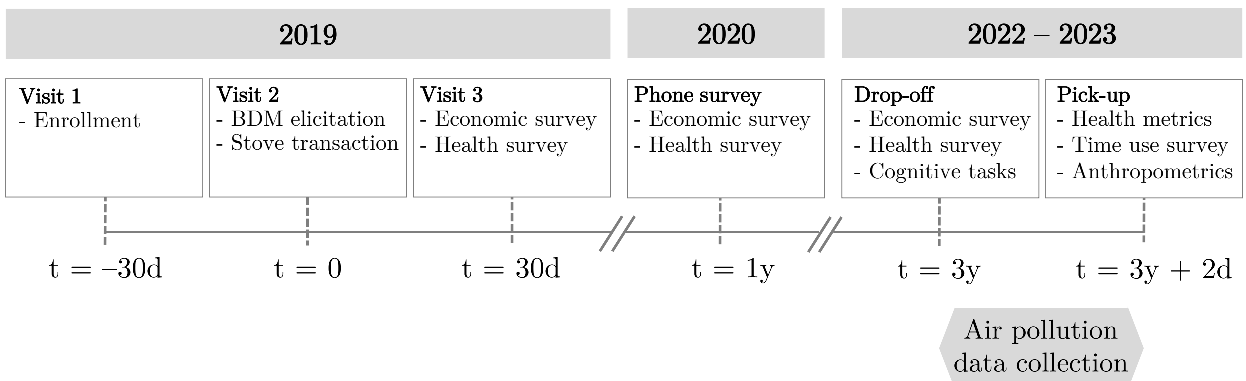
Our health-related outcome variables and the surveying methodology we use to measure them are informed by an extensive public health literature. The Guatemala RESPIRE trial found impacts on blood pressure (McCracken et al., 2007), and more recently an experiment in urban Nigeria found that an improved stove can reduce blood pressure among pregnant women (Alexander et al., 2018). Chang et al., 2015; Kubesch et al., 2015; Soppa et al., 2014) document an association between air pollution and blood pressure within 1–2 hours of high pollution exposure.

Recent RCTs in rural Malawi and rural Guatemala found that improved stove adoption can reduce pneumonia in adults and in children (Mortimer et al., 2016; Smith-Sivertsen et al., 2009). In settings where the technology to formally diagnose pneumonia is unavailable, the literature recommends three methodologies to diagnose pneumonia. The first is to inquire about diagnoses made by health professionals. The second is to ask about symptoms related to respiratory distress in order to make an attempted diagnoses of an acute respiratory infection (ARI), which can then be cautiously interpreted as a presumed pneumonia diagnoses. This methodology is standard for, among others, the World Health Organization, the USAID Demographic and Health Survey (DHS) program, and UNICEF.[8] Finally, oximetry readings have been found to be a cost-effective approach to screening for respiratory infections (Floyd et al., 2015; National Library of Medicine, 2021; Van Son and Eti, 2021).

3 Study design and methodology

The study consists of baseline and short-term follow-up activities conducted in 2019, a medium-term follow-up conducted in 2020, and a long-term follow-up conducted in 2022–2023. Figure 2 presents an overview of the study elements included in each survey round.

Figure 2: Timeline of field activities



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

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

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

impacts on their health, and how much adoption of an energy efficient stove might improve their health.

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

In July-August 2019, approximately one month after the main visit, enumerators conducted a short-term endline survey. In 2020, enumerators conducted a medium-term phone survey.[9] These surveys ask about a range of socioeconomic outcomes, including charcoal expenditures, savings (in bank accounts, mobile money accounts, or rotating savings groups), as well as the same health symptoms questions asked during the baseline surveys.

In 2022-2023 enumerators conducted a long-term survey round. Table 1 presents summary statistics collected during these surveys. Enumerators were able to reach 775 of the 942 respondents they attempted to reach, and successfully surveyed 702.[10] 95% of respondents were surveyed between 3.4–3.7 years after the original main visit.

The long-term survey round consisted of two surveys, the second approximately 48 hours after the first. The surveys were designed to take quantitative measurements of three long-term outcomes: air pollution, physical health, and cognition. An accompanying socioeconomic survey included questions on charcoal expenditures, Jikokoa ownership and usage, other cooking technology ownership, maintenance, food cooked, home heating, in-network Jikokoa purchases, savings, income, and work activities.

To match high-frequency pollution data to specific activities, the second survey included a time use module inquiring about which activities the respondent was engaged in for each hour between the two surveys, whether they were indoors or outdoors during that 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.[11]

The time use data indicate that households primarily cook indoors: 86% of time spent cooking takes place indoors, on average. However, this hides significant heterogeneity, which appears correlated with stove emissions. For the 278 households who report using an LPG or electric stove at least once in the time use survey, only 5% of the time spent cooking with such a stove is spent

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

[10] 13 of the 955 respondents completed the main visit in 2019 but removed themselves from the study between 2019 and 2022. 167 respondents could not be contacted in 2022-2023 despite repeated phone calls to their phone numbers or any other phone numbers they had used for earlier SMS surveys or MPESA payments. Physical attempts to track individuals residing in the study areas were hampered by the recent demolitions of housing in Nairobi's settlement areas (The Star, 2023). Respondents who were contacted but who did not complete a 2022-2023 survey did not do so for various reasons, including nonconsent, migration, physical incapacitation, or death. As a rule we attempted to survey any respondent still residing in Kenya. Attrition is balanced by treatment assignment, take-up, and baseline health (Table A21).

[11] There are modest differences in the types of technologies used during different types of day, with LPG used more in the mornings and a charcoal jiko or Jikokoa used more in the evenings (Figure A1). Anecdotally, this is due to a preference for a fast-lighting stove (which the LPG stove is, in comparison to biomass) in the morning, for a small meal or hot beverage, and a longer-cooking stove when preparing larger meals.

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.

outdoors. Conversely, for the nearly 500 households who report using a Jikokoa, traditional wood or charcoal jiko at least once in the time use survey, more than 20% of time spent cooking with such a stove is spent outdoors. It is plausible that respondents are more likely to choose to cook indoors when using a relatively cleaner stove, and that this reduces the beneficial impact of an improved stove as emissions are more likely to build up when cooking indoors. Our results should therefore be interpreted as factoring in any such behavior change induced by stove adoption. Similarly, our results should be interpreted as factoring in other relevant behavior changes such as opening doors or windows in order to increase household ventilation rates. Estimating the causal impact of stove adoption on propensity to cook indoors suggests a reduction of 5 percent (on a control mean of 90 percent) but this reduction is not statistically significant (p-val=0.29).

3.1 Causal identification

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

During visit 2, enumerators used a Becker-DeGroot-Marschak (BDM) mechanism (Becker, Degroot, and Marschak, 1964) with a guided binary search to elicit WTP for the Jikokoa stove. Respondents whose WTP was at least as high as their randomly assigned price (the market price of USD 40 minus the randomly assigned subsidy) then adopted the stove.[12]

The credit treatment doubled WTP (95% CI: 93%–114% increase) while the attention treatment had no effect on WTP (Figure A2 shows the full distributions of WTP by treatment group). The randomized credit and subsidy treatments were highly predictive of improved stove adoption: among those in both the high subsidy and the credit treatment group 93% adopted the Jikokoa, whereas among those in both the low subsidy and the credit control group only 8% did. To estimate the causal effect of improved stove adoption on long-term outcomes we use the randomly assigned subsidy, the credit treatment assignment, and their interaction as instruments for adoption. We report weak instrument F-statistics where relevant—the first stage is generally strong.

Using the randomly assigned subsidy as an instrument, Berkouwer and Dean (2022a) find that adoption of the Jikokoa causes a 39% reduction in charcoal usage, generating $120 in fuel savings per year—approximately one month of average respondent income.

3.2 Air pollution exposure concentrations

We measure particulate matter (PM1.0 and PM2.5) and carbon monoxide (CO ppm). The PM monitor is a Purple Air II Air Quality Sensor (PA-II) that takes one measurement per minute (Panel A of Figure A3).[13] The CO monitor is a Lascar EL-USB-CO Carbon Monoxide Data Logger that takes one measurement every two minutes (Panel B of Figure A3).[14] To confirm device accuracy and precision, a test of co-located readings reveals devices are strongly correlated with a small and generally stable gap between some devices (Figure A4). For this reason we include device fixed effects in all regressions.[15] Figure 3 maps respondents' interview locations across Nairobi

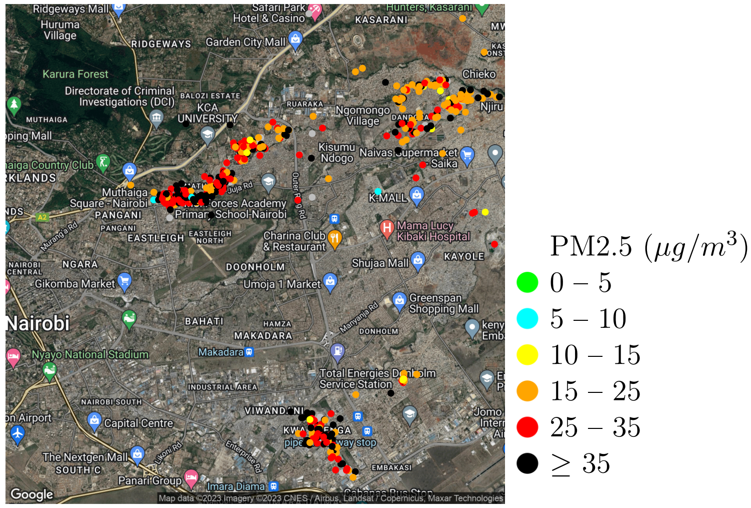
[12] 98.6% of respondents who 'won' the stove through the BDM actually adopted the stove.

[13] 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 PAII calibration methodology from Giordano et al. (2021) and Ward et al. (2021) to correct for humidity and local air composition. Building on Tryner et al. (2020), if the difference between the a and b readings is at least 25% and at least 15 $\mu g/m^3$ the reading is removed from the sample (1.7% of readings).

[14] Each CO monitor has an independent calibration factor. Monitors were re-calibrated every two months, between survey breaks. We include monitor fixed effects in all regressions.

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

Figure 3: Average air pollution (PM 2.5) for participants by their home locations



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

according to their average air pollution exposure.[16] Collecting pollution exposure over a 48-hour period captures HAP as well as AAP generated by industrial facilities, traffic, or other sources in urban Nairobi.

Following best practices (Gordon et al., 2014; Gould et al., 2022), we designed the deployment methodology to collect exposure as experienced by respondents rather than stationary monitoring of kitchen concentrations. To achieve this, we used procedures developed by the Berkeley Air Monitoring Group (Johnson et al., 2021). During the first endline survey we provided each respondent with a small mesh backpack containing the two devices (Panels C and D of Figure A3). 48 hours later the enumerators then picked up the devices, downloaded the data, recharged the 48-hour battery pack, and placed them in a new backpack before re-deploying it with a different respondent.[17] Respondents were asked to wear this backpack continuously whenever feasible, or to keep it within one meter, at waist level, when wearing it was infeasible. We did not quantitatively monitor backpack wearing, as this would have required installing GPS trackers on the backpacks which we felt violated participants' privacy. However, qualitatively, enumerators reported generally high backpack wearing.[18] Our methodology is in line with best practices from the air pollution monitoring literature (Burrowes et al., 2020; Chillrud et al., 2021; Gould et al., 2023).

One concern with deploying conspicuous sensors is that respondents may be more self-conscious

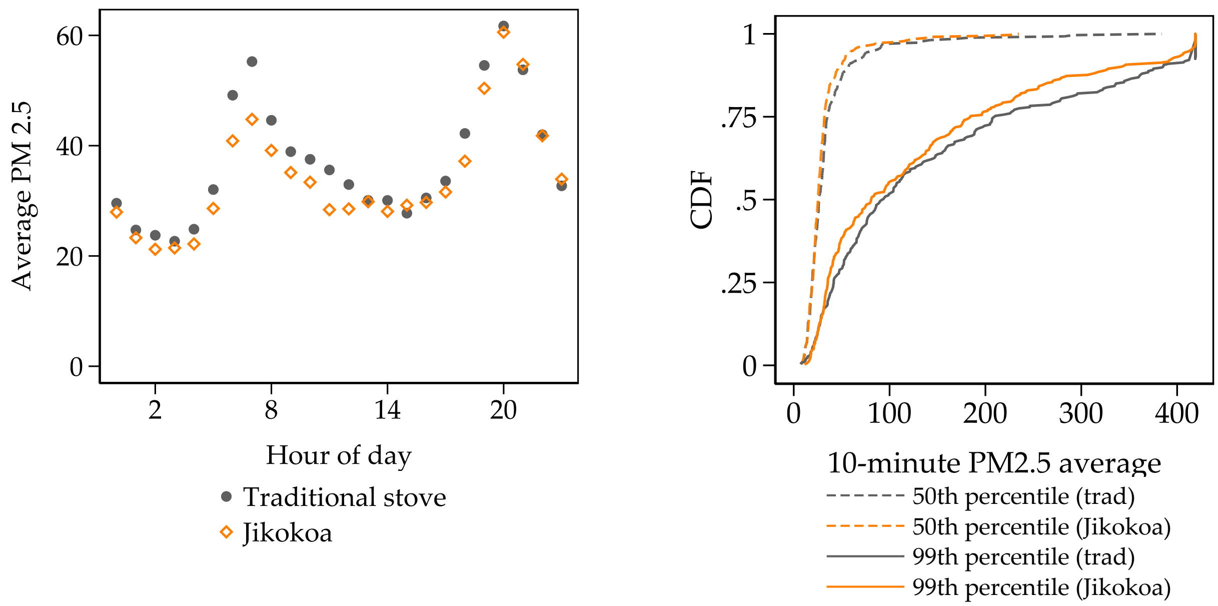
[16] 60 survey respondents were located in rural areas and are not shown in Figure 3.

[17] 85% of respondents held the device between 45–50 hours. Air pollution data are missing for 45 respondents who only had time to complete a single survey.

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

Figure 4: Particulate matter (PM2.5, in $\mu g/m^3$) pollution by Jikokoa ownership

A) Over the hours of the day   B) Distributions of 50th and 99th percentiles of 10-minute averages (by household)



Panel A shows average PM2.5 air pollution, by hour and endline Jikokoa ownership, as collected by respondents wearing backpacks for on average 48 hours. Figure A5 presents the same for PM1.0 and CO.

of their own cookstove usage and alter their cookstove use in response, thereby biasing the effect we observe away from the true effect—a concern known as the Hawthorne effect. Existing research has identified this effect in the monitoring of health technologies such as cookstoves or latrines (e.g. Clasen et al., 2012; Simons et al., 2017). For this reason we administer questions about charcoal expenditures and cookstove usage during the first survey, before deploying the devices so that these responses would not be affected by any potential effect.

Panel A of Figure 4 presents average pollution over the hours of the day by whether or not the respondent owned a Jikokoa. The levels and diurnal patterns of PM2.5 and PM1.0 follow the air pollution patterns documented by Pope et al. (2018) in urban Kenya. We do not observe any meaningful seasonal heterogeneity in air pollution over our sample period.

To better understand the peak pollution faced by our sample, we compute the average exposure during each 10-minute window for each respondent in our data. Panel B of Figure 4 shows the cumulative distributions of each respondent's 50th (median) and 99th percentile 10-minute average, with the 99th percentile 10-minute average representing approximately the worst 15 minutes of one's day. For 89% of respondents, their median 10-minute average is below 50 $\mu g/m^3$. However, for most respondents, the worst 15 minutes of their day is well above 84 $\mu g/m^3$—in fact, this exceeds 200 $\mu g/m^3$ for 23% of respondents.

Matching hourly time use data and hourly pollution data indicates that PM2.5 is lowest in the hours when sleeping (32 $\mu g/m^3$) and highest in the hours when cooking (46 $\mu g/m^3$) on average (Table A2).

3.3 Physical health

Enumerators record systolic and diastolic blood pressures using a sphygmomanometer, following procedures set by the CDC NHANES (2019). 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. The analysis uses direct measures of systolic and diastolic blood pressure as well as indicators for having hypotension (low blood pressure, defined as $<$90/60 mmHg), stage 1 hypertension (130-139/80-89 mmHg), and stage 2 hypertension ($\geq$ 140/$\geq$ 90 mmHg), as defined by the American Heart Association and the American College of Cardiology (Goetsch et al., 2021). Enumerators use pulse oximeters (blood oxygen saturation monitors) to record haemoglobin oxygen saturation.[19]

The survey furthermore asks a large set of health questions, following the methodology from field experiments in the public health literature (see for example Checkley et al., 2021; Smith-Sivertsen et al., 2009; Tielsch et al., 2016 and others). This includes a set of 10 yes/no questions asking if a medical professional had diagnosed the respondent with various medical diagnoses (including pneumonia, asthma, or other lung disease), of which we only keep diagnoses that were made in the past three years (since the original experiment). It includes a set of 29 yes/no questions asking if the respondent experienced specific symptoms in the past 4 weeks (including fever, persistent cough, stomach pain, or rapid weight loss, as well as symptoms required to make a presumed pneumonia diagnosis). The survey also asks about perceptions of health impacts, and frequency and financial costs of hospital visits. For female respondents, the enumerator also inquired about recent pregnancies, birth outcomes, and any recent newborns' weight and length. We use these self-reports to generate a standardized adult physical health index.

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. The adult respondent is asked similar questions about symptoms any child(ren) may have had, which are then combined into a standardized child physical health index. The enumerator finally measured child and adult height, weight, and arm circumference as indicators for physical child development and for parental controls, respectively. For each child under 5 who lives in the home the survey asks about overall health, basic health symptoms (specifically those that permit a presumed pneumonia diagnoses, including fever, vomiting, and cough), school attendance, medical diagnoses.

Table 1 presents summary statistics on health outcomes. In addition, 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. To control for diurnal patterns in health outcomes such as blood pressure, health regressions control for hour of day during which each survey

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

was administered.

3.4 Cognition

To provide an assessment of basic adult and child cognitive functions, we use three instruments. First, we use the Reverse Corsi Block task to measure working memory (Brunetti, Del Gatto, and Delogu, 2014). Second, we use Hearts and Flowers to measure response inhibition (Davidson et al., 2006). Third, we use the d2 task for sustained attention (Bates and Lemay Jr., 2004; Brickenkamp and Zillmer, 1998). For detail on these cognitive assessments, see Appendix C.

The analysis uses an adult cognitive ability index by standardizing each component to have a mean of 0 and a standard deviation of 1 and then taking the average across the outcomes, as well as a child cognitive ability index by standardizing each component to have a mean of 0 and a standard deviation of 1 and then taking the average across the outcomes.

4 Causal impacts

To estimate the causal effect of adoption of the energy efficient charcoal cookstove on health outcomes, we employ an instrumental variables approach where we use the randomly assigned BDM price (P_i), the randomly assigned credit treatment status (C_i), and their interaction (P_iC_i) as instruments for stove ownership d_i. These were the two random treatments found to have a statistically and economically large effect on stove adoption in Berkouwer and Dean (2022a).[20] Since P_i and C_i are both randomly assigned, this regression identifies the causal effect of stove adoption on the outcomes of interest. Econometrically, this proceeds as follows:

$$y_i = \beta_0 + \beta_1[\hat{d}_i \sim P_i, C_i, P_iC_i] + \beta_2 X_i + \epsilon_i \tag{1}$$

where $\hat{d}_i$ is a dummy for (endogenous) adoption. X_i is a vector of controls consisting of household baseline charcoal spending, savings, income, risk aversion, credit constraints, education, baseline self-reported health status, household adults and children, and a geographic neighborhood indicator assigned using a K-means clustering algorithm. The outcome variable y_i varies across regressions. Regressions include fixed effects for hour of day and/or date, week, or month of year surveyed as relevant.

Note that $\hat{d}_i$ 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

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

own one at endline are attributed to the (smaller) treatment group. We present both estimates where relevant but use ownership as of the long-term follow up in most regressions.

4.1 Impacts of random treatments on stove ownership

Panel (A) of Table 2 shows the causal impact of 2019 Jikokoa adoption on long-term ownership of the Jikokoa and other stove types. 90% of respondents who did not adopt a Jikokoa during the main visit also do not own one during the long term endline, and 83% of respondents who adopted a Jikokoa initially also own one three years later. This persistence generates a strong first-stage to study the impacts of the Jikokoa on other outcomes, with weak IV F-statistics between 20 and 50 depending on the specification (Table A3 presents the first stage).

Jikokoa adoption does not appear to meaningfully increase adoption of other modern cooking technologies such as liquefied petroleum gas (LPG), bio-ethanol, or electric stove ownership, though we cannot rule out modest increases. We thus find limited evidence of the 'energy ladder' theory that initial adoption of an improved biomass stoves can act as a stepping stone towards even cleaner cooking technologies (Hanna and Oliva, 2015), nor of the converse theory, that adoption of an intermediary technology can slow adoption of a more advanced technology (Armitage, 2022). The average household owns 1.9 unique stove types, indicating some degree of 'fuel stacking' (simultaneous ownership and/or use of cooking technologies that use multiple types of cooking fuel). LPG ownership has risen sharply in recent years, with 57% of respondents now owning an LPG stove, potentially as a result of a government LPG subsidy program (IEA, 2022). The estimates take any stacking at face value, estimating the causal effect of improved cookstove adoption factoring in any continued use of existing stove (rather than an estimate of a strict switch from an existing stove to an improved stove).

These results imply that a subsidy for the Jikokoa is an extremely cost-effective means of reducing carbon emissions because the subsidies were marginal for the decision of the vast majority of households while not crowding out adoption of other emissions reducing options. To illustrate, consider a back of the envelope calculation of the emissions reductions from distributing 100 of the stoves for free. One year after our initial distribution 98.3% of those who adopted the stove with a subsidy still had their Jikokoa while 4.2% of those who did not receive a subsidy subsequently purchased the stove at market price (Berkouwer and Dean, 2022a). Using the proportion of those who did not receive a subsidized stove during the experiment but subsequently purchased at market price as a measure of the inframarginality of subsidy gives a net increase of 94.1 stoves in this first year. Now suppose that after this one year endline, ownership immediately changed to the 84% and 10% ownership shares we find in this 3.5 year endline. This implies a lower bound on the net impact of increasing adoption by 73 stoves for the following two and a half years. In Berkouwer and Dean, 2022a we estimate that adopting a Jikokoa reduces household emissions by 3.5 tons of carbon dioxide equivalent per year. Thus we would expect distributing 100 stoves stoves to reduce emissions by at least 968.1 tons of carbon dioxide equivalent. Using the market cost at the time of the study of $40 per stove this yields an upper bound on the cost of reducing carbon of $4.13 per

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 Jikokoa ownership (as of 2022 or 2019) on outcomes recorded during the 2022–2023 endline surveys. Each row is a s 2-SLS regression that uses the randomly assigned (BDM) price, credit treatment status, and their interaction as instruments for the (endogenous) cookstove adoption variables. Demographic and 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, and age as decade binary variables (designed to capture non-linear impacts of age). Regressions also control for field officer fixed effects. Table A4 presents additional socio-economic outcomes relating to savings and in-network adoptions.

ton of CO2 equivalent.

Panel (B) of Table 2 presents the impact of stove adoption on various socioeconomic outcomes. Column (2) uses 2022 Jikokoa ownership as the endogenous variable while Column (3) uses 2019 Jikokoa adoption as the endogenous variable. Among the urban sample, improved cookstove ownership causes a USD 1.65 reduction in weekly charcoal expenditures, about a 44 percent reduction relative to the control group (Table A4). This adds up to approximately USD 86 per year—statistically and economically a large result, though the estimate is slightly lower than short- and medium-term impacts (Berkouwer and Dean, 2022a). Rural residents spend less than half as much on charcoal per week as urban residents.[21] The combined treatment effect for the full sample is therefore slightly lower, USD 1.50 per week on average. In terms of other behavioral outcomes, we see no impacts on time spent on various activities—such as sleeping, working, eating, or walking—each day (Table A5). Taken together these results demonstrate that the stoves have both large private and social benefits before considering their impact on health.

In addition, Jikokoa adoption increases the propensity of individuals in an adopter's network to adopt the stove. Specifically, it roughly doubles the number of Jikokoa stoves owned by members in a respondent's network such as friends and family (see Table A4 for more detail), driven primarily by an increase in ownership by neighbors.

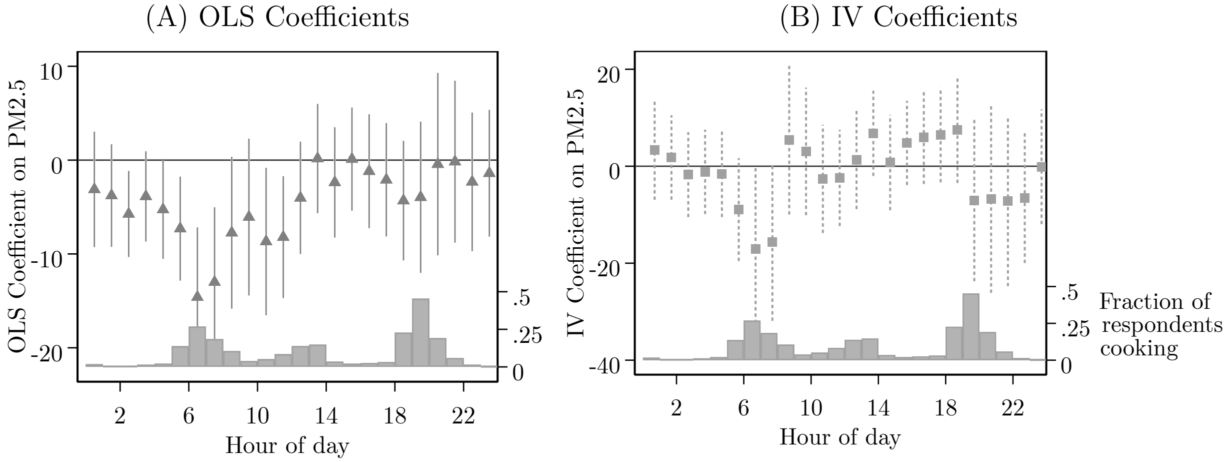
4.2 Impacts of stove ownership on air pollution

The link between stove ownership and air pollution varies significantly across hours in the day. Panel (A) of Figure 5 presents a standard OLS panel fixed effects regression, estimating a separate coefficient for each hour of the day. Panel (B) uses the instrumental variables approach to similarly estimate a separate causal estimate for each hour of the day. For comparability, both panels also present a histogram of the number of people who reported cooking during a given hour in the time use survey. Both graphs display three key characteristics. First, improved stove ownership reduces air pollution between 5–8am. Second, adoption does not appear to have caused any meaningful impact during any other hours of the day. Third, the timing of the reductions line up remarkably well with when respondents generally report to be cooking.

Figure 5 also reveals a modest reduction in air pollution concentrations during dinnertime between 7–9pm, though this reduction is significantly smaller than the effect during breakfast time. The lack of effect during dinnertime is not driven by differences in cooking technologies used during the different meals: during all daytime hours, a Jikokoa is being used by approximately 30% of respondents that are cooking, a traditional Jiko is being used by approximately 27% of respondents, and an LPG stove is being used by approximately 23% of respondents (Figure A1). Instead, we hypothesize that the lack of reduction in dinnertime pollution exposure is due to diurnal variation in planetary boundary layer height (PBLh). A lower PBLh weakens the exchange of air between the earth's boundary layer and the free atmosphere, trapping particles closer to earth's surface. NASA MERRA-2 satellite measurements indicate that PBLh in Nairobi is on average 1,600 meters during the morning hours of 5–8am but on average 60 meters during the evening hours of 7–9pm (Figure A6). Previous research has documented a strong relationship between PM2.5 and PBLh (Dhammapala, 2019; Dobson et al., 2021; Manning et al., 2018). Low PBLh during the evening

[21] This is consistent with anecdotal and census evidence indicating that households living in rural areas are more likely to use firewood to cook as this can often be gathered at little to no cost.

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



Panel (A) reports coefficients from an OLS regression of PM2.5 on Jikokoa ownership. Panel (B) reports coefficients from an equivalent IV regression, using subsidy, credit treatment status, and their interaction as instruments. In line with the regression results below, both regressions include week FE, device FE, and the interaction of and hour-of-day by day-of-week by neighborhood FE, as well as the same demographic and socioeconomic controls listed in Table 2. The gray bars report the fraction of respondents who report cooking during any given hour in the time use survey. Table 3 presents regressions pooling hours 6–8am and 6–9pm which are the most common cooking hours, for PM2.5 (Panel A) and CO (Panel B).

may saturate the boundary layer and reduce the marginal impact of cookstove emissions reductions, but more research is needed to confirm this channel.

Table 3 aggregates pollution exposure data for each individual and estimates the causal impact of stove adoption on three key moments of pollution exposure. Columns (1) and (5) estimate the causal impact on median exposure while Columns (2) and (6) estimate the causal impact on mean exposure, taken over all (minute- or 2-minute level) readings. Columns (3) and (7) consider the maximum of hourly average exposure while Columns (4) and (8) consider the 99th percentile of 10-minute averages. Panel A considers the full 45–50 hours during which the respondent was wearing the device, while Panel B limits the data to the hours during which the respondent self-reported cooking in the time use survey (Figure 5 also presents results on all non-cooking hours and on cooking hours defined uniformly as 6–8am and 6–9pm, when most respondents report cooking).

Two key patterns emerge in the PM2.5 data results. First, there is a large and statistically significant reduction of 49 $\mu g/m^3$ in the 99th percentile of 10-minute means while cooking (Column 4 of Panel B), which corresponds to around a 40% reduction in the marginal emissions increase from cooking (compared to median non-cooking exposure) when compared with the control group. In other words, Jikokoa reduces the peak emissions from cooking by around 40%, which approximately matches the 37% reduction in charcoal expenditures identified in Table 2: PM2.5 emissions from cooking appear to reduce approximately linearly in proportion to charcoal usage. Improved cookstove adoption also reduces the time spent cooking (Column (1) of Table A8); anecdotally this is driven by the fact that the improved stove takes less time to heat up. As a result, the reduction in pollution in maximum hourly average is even larger—48%—as this factors in both the reduced peak levels as well as a reduction in the time spent near the stove during the most polluted cooking hour (Column 3 of Panel B). These patterns are economically and statistically similar when the data are analyzed in logs (Table A6).

Second, however, there are no detectable effects on any of the other hours of the day, when ambient pollution remains high (Panel B of Table A7). As a result, despite large emissions reductions during cooking, there is only a 2% reduction in aggregate average exposure, and it is not statistically significantly different from zero (Column 2 of Panel A). The lack of impact on aggregate average air pollution can be reconciled with the relatively small amount of time spent cooking daily: respondents cook for 9% of the day (2 hours) on average. Median non-cooking exposure to PM2.5 is around 25 $\mu g/m^3$ (this is in line with Pope et al. (2018), who find urban roadside levels of 36.6 $\mu g/m^3$ and background of 24.8 $\mu g/m^3$). Indeed, the coefficient in Column (2) of Panel A is close to 9% of that reported in Column (2) of Panel B. In this context, the reduction in cooking-related pollution cause only a small reduction and statistically undetectable in total pollution exposure.

Table 3: Causal impact of cookstove adoption on pollution exposure

Panel A) All hours

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

Panel B) When self-reporting cooking

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

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. All PM2.5 regressions have 590 observations and a Weak IV F-statistic of 48. All CO regressions have 607 observations and a Weak IV F-statistic of 49. 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 the same demographic and socioeconomic controls listed in Table 2 and a fixed effect for the specific LASCAR or PA-II device used for that respondent. Table A7 presents the same for when self-reporting not cooking as well as for the hours between 6–8am and 6–9pm specifically, which is less prone to recall bias. Table A6 presents all four outcomes in logs. We omit presenting CO in log because 55% of 10-minute average observations and 37% of 1-hour average observations equal 0.

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

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

Columns (5)–(8) of Table 3 indicate no impacts on CO. This is in line with recent independent laboratory tests scoring the Jikokoa Tier 3 for PM2.5 but Tier 1 for CO (CREEC, 2022). A stove's CO output generally depends on its rate of oxygenation: higher oxygen inflow increases the production of CO_2 and reduces the production of CO while cooking. Per the company's engineers, the lack of reduction in CO output results from a desire to increase the durability of the stove by limiting peak cooking temperatures to 700°C. While this improves durability, it limits oxygenation.

It is worth noting that inverting these statistics to be represented as time above thresholds (for example, 'minutes per day where a participant is exposed to PM2.5 in excess of 100 $\mu g/m^3$') dramatically reduces the power of the estimation, as big changes that happen entirely below or entirely above the threshold will be ignored and only movements across the threshold will generate a treatment effect (Table A9). When trying to answer regulatory or health questions, looking at averages or other moments in the distribution can often generate more precise statistical results than relying on data on thresholds.

4.3 Impacts of stove ownership on health

Table 4 presents the primary estimates from the instrumental variables approach described in Equation 1, of the impact of stove adoption on health outcomes, controlling flexibly for age and linearly for other socioeconomic outcomes measured at baseline. Column (2) uses 2022 Jikokoa ownership as the endogenous variable while Column (3) uses 2019 Jikokoa adoption as the endogenous variable. The first five outcomes are quantitative measurements. The next seven outcomes are self-reported health outcomes, while the final three outcomes measure health expenditures. Following our pre-

[22]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
Average systolic blood pressure	122.16	0.49	0.18	696
	[18.97]	(3.30)	(2.41)	
Average diastolic blood pressure	81.32	0.58	0.36	696
	[11.73]	(2.15)	(1.57)	
Hypertension: Stage 1 or higher (>130/80)	0.51	0.02	0.02	696
	[0.50]	(0.09)	(0.07)	
Hypertension: Stage 2 or higher (>140/90)	0.27	-0.02	-0.02	696
	[0.44]	(0.08)	(0.06)	
Blood oxygen	96.61	0.31	0.20	696
	[2.53]	(0.37)	(0.27)	
Number of non-respiratory health symptoms	1.09	-0.24	-0.18	702
	[1.54]	(0.25)	(0.19)	
Non-respiratory health symptom index	-0.00	-0.03	-0.03	702
	[1.00]	(0.19)	(0.14)	
Number of respiratory health symptoms	1.70	-0.48**	-0.36**	702
	[1.76]	(0.23)	(0.17)	
Respiratory health symptom index	-0.00	-0.24*	-0.18*	702
	[1.00]	(0.13)	(0.10)	
Health diagnoses index	0.00	0.13	0.10	702
	[1.00]	(0.16)	(0.12)	
Number of health diagnoses	0.30	0.13	0.10	702
	[0.58]	(0.09)	(0.07)	
Cognitive index	-0.00	-0.01	-0.02	587
	[1.00]	(0.15)	(0.12)	
Non-hospital health expenditures (USD)	4.34	0.80	0.56	702
	[7.64]	(1.07)	(0.78)	
Hospital visits in past 30 days	0.33	-0.01	-0.01	702
	[0.57]	(0.09)	(0.07)	
Hospital visit expenditures (USD)	3.39	1.03	0.79	702
	[11.17]	(1.48)	(1.08)	

Each row is an instrumental regression wherein endline modern stove use is instrumented for with randomly assigned price, credit treatment status, and their interaction. Regressions control for the same demographic and socioeconomic characteristics as listed in Table 2. Regressions also control for hour of day of the second visit, where blood pressure and blood oxygen were recorded. Table A10, Table A11, Table A12, and Table A13 present detailed results on the components of symptoms, diagnoses, and cognitive indices. Outcomes for children are presented in Table A14 and Table A15.

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 A10 present more detailed results on pollution-related symptoms). Section 4.5 presents evidence for why these results are unlikely to be driven by experimenter demand.

However, we identify no long-term health improvements in quantitatively measured outcomes such as blood oxygen and blood pressure, self-reported non-respiratory symptoms, and self-reports about any diagnoses made by a medical professional during a hospital visit (Table A11 and Table A12 present more detailed results on non-pollution related symptoms and medical diagnoses, respectively). Similarly, we find no effect on the number of hospital visits, hospital-related expenditures, or any of the cognition outcomes (Table A13).[23]

We cannot detect a statistically significant impact on a range of child health outcomes, including weight, height, and arm circumference, a range of self- or parent-reported symptoms, and two types of attempted pneumonia diagnoses (Table A14), neither among children under 10 nor when restricting the sample to just children age 5 or under who are more likely to stay at home during the day (Table A15).

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

4.4 Heterogeneity of health impacts

We do not find evidence of heterogeneity in treatment impacts along the lines of baseline health, baseline beliefs about future health impacts, age, WTP, or baseline charcoal expenditures (Table A16). Background ambient pollution is 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 whose 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; the relationship between health and pollution could be concave elsewhere along the distribution (Table A17).

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

Since ambient pollution levels are generally lower in rural areas than in urban areas, study participants residing in rural areas may experience larger proportional pollution improvements. To examine whether health impacts are different for study participants residing in rural areas, we estimate the causal impact of adoption on health outcomes just among this sample. We do not find evidence of health improvements among this sub-sample—in fact, most point estimates point in the opposite (Table A18). We refrain from over-interpreting this result because the rural sample is very small ($n = 53$) and because moving to a rural area is an endogenous choice that may therefore introduce bias in the estimation.

The results on pollution and health furthermore point to potentially important heterogeneity in the impacts of pollution exposure on health. Specifically, the reduction in peak exposure may reduce short-term self-reported symptoms such as having a sore throat, but the lack of reduction in aggregate average pollution exposure may explain the lack of impacts on chronic or quantitative health outcomes, despite 3.5 years of sustained use of reduced peaks in air pollution. Section 5 explores this possible relationship in more detail.

4.5 Robustness tests

A critical concern when using self-reported data is whether self-reports are driven by experimenter demand. Participants who received a (sometimes very heavily) subsidized cookstove might be more inclined to report better health than those who did not. While we cannot rule out some amount of experimenter demand, several factors weigh against this fully explaining the effects. First, we test whether those with higher subsidies are more likely to report positive health. 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 A19). Second, self-reported health improvements arise primarily through respiratory rather than non-respiratory symptoms: participants would thus have to be sophisticated about which types of health symptoms they report improvements in. Third, the relationship between health and pollution is similar in magnitude when constraining the sample to either just adopters or to just non-adopters, though the estimates are no longer significant due to the smaller sample size (Table A24 and Table A25).

702 of the 942 respondents (75%) were surveyed successfully during the three-year follow-up survey. 60 of these respondents had moved outside Nairobi to locations where our survey team could still reach them. 65% of those who were not surveyed could not be contacted; the remainder were not surveyed because they said they were unavailable, withdrew from the study, or relocated to locations outside of the survey team's reach (Table A20). Attrition is not correlated with their randomly assigned BDM price, credit treatment assignment, initial Jikokoa stove adoption, or baseline health outcomes (Table A21). Attrition is slightly higher among respondents with fewer children, fewer household members, and younger respondents (such respondents may more easily move around, making them harder to track).

5 The relationship between pollution and health

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

Instead, we provide some evidence by using standard OLS regressions to estimate three key moments: average pollution exposure (in 100 $\mu g/m^3$), peak pollution exposure (defined as the highest hourly average recorded, in 100 $\mu g/m^3$), and the duration of high pollution exposure (defined as the number of hours pollution was above in 100 $\mu g/m^3$). Table 5 presents the results. Columns (4) and (6) control for average pollution to look at the effect of peakiness as distinct from higher average pollution.

Mean or median PM2.5 air pollution are not correlated with self-reported health symptoms,

Table 5: Correlation between health and mean, median, maximum, and duration of PM2.5 exposure

	Mean SD	Mean Pollution (SD)	Median Pollution (SD)	Max Hourly Pollution (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 control for the same socioeconomic and demographic characteristics as in Table 2, as well as fixed effects for the specific PA-II device used, field officer fixed effects, month of survey, and final willingness to pay for the Jikokoa in 2019. Hypertension refers to stage 1. Table A22 provides the same for CO. Table A23 provides a version with additional detail. Table A10, Table A11, and Table A12 present detailed results on symptoms and diagnoses. Table A24 and Table A25 present the same for whereas maximum hourly pollution is. This points to important heterogeneity in the impacts of maximum air pollution exposure rather than mean daily levels that were investigated in much of the literature studying ambient air pollution, such as Chay and Greenstone (2003), Clay, Lewis, and Severnini (2022), Currie and Walker (2011), Deryugina et al. (2019), Ebenstein et al. (2017), Greenstone and Hanna (2014), Isen, Rossin-Slater, and Walker (2017), and Schlenker and Walker (2015).

6 Conclusion

Academic literatures on indoor and outdoor air pollution have primarily focused on these topics in isolation, despite the fact that many of the world's urban poor face both on a daily basis. Importantly, the presence of high ambient air pollution may dampen the health improvements derived from the private adoption of improved air quality technologies. Disentangling the health impacts of household and ambient air pollution has important implications for whether urban environmental health can be improved through private actions or requires government intervention addressing negative environmental externalities.

We investigate the interaction of these two sources of individual pollution exposure by leveraging an urban randomized experiment of improved biomass cookstoves among 700 households in Nairobi, Kenya. The analyses generate several key findings.

First, the subsidies yield persistent increase in adoption of a more energy efficient biomass cookstove. This persistence means a policy of distributing stoves for free would likely abate emissions at a cost of approximately $4 per ton, significantly cheaper than most alternatives available today. In addition, the stoves continue to generate large co-benefits: urban households continue to save on average USD 1.65 (44%) in weekly energy expenditures

We also find that the stove causes a large reduction in air pollution generated during cooking hours, even more than three years after initial adoption. Households experience a 0.24 standard deviation improvement in self-reported respiratory symptoms.

However, since we observe no reduction during the remaining 22 hours of the day, and given the high levels of ambient pollution in this urban context, we see only a very small and statistically insignificant effect on aggregate air pollution exposure. These washed out pollution impacts can explain the comprehensive lack of impacts on a host of quantitative health measurements (including blood pressure and blood oxygen) and self-reported diagnoses of chronic diseases such as pneumonia.

The limited contribution of indoor air pollution to aggregate air pollution when compared with outdoor air pollution departs from previous research on this topic (Fisher et al., 2021) and has important policy implications (Gill-Wiehl and Kammen, 2022).

Adoption of clean cooking technologies may have a larger impact on health in rural areas, where ambient pollution levels tend to be lower. In Kenya, background is approximately 9 $\mu g/m^3$ Pope et al. (2018). Even assuming participants cook for twice as many minutes each day in rural areas as in urban areas, this would lead to a 22% reduction in aggregate exposure. Corroborating this back-of-the-envelope calculation, and understanding the impacts on health, is left as future work.

The results above suggest that the urban poor have only limited ability to improve their environmental health through the private adoption of improved technologies. Instead, improving chronic and long-term health will depend on the reduction of ambient air pollution, which will require government intervention addressing the negative pollution externality caused by economic activity.

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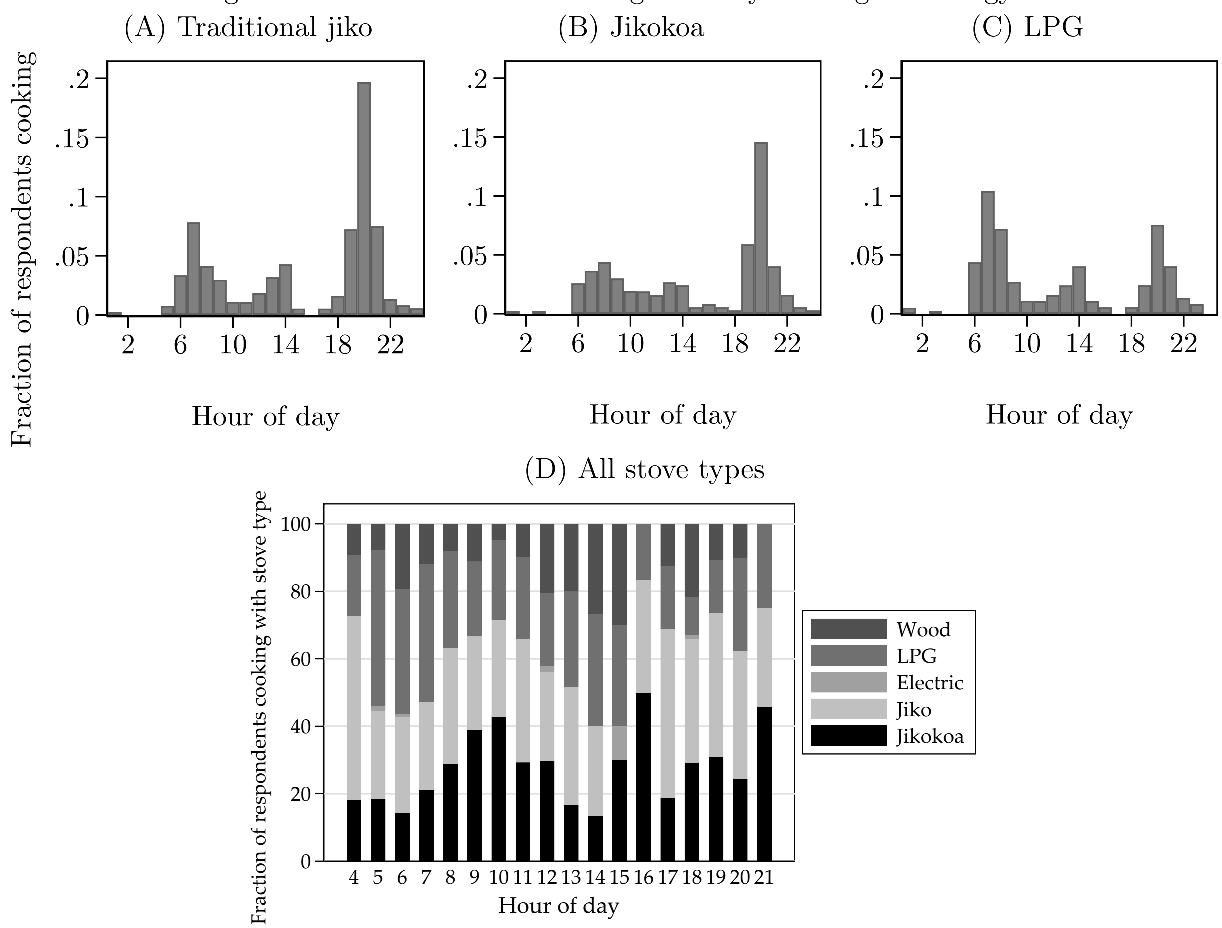
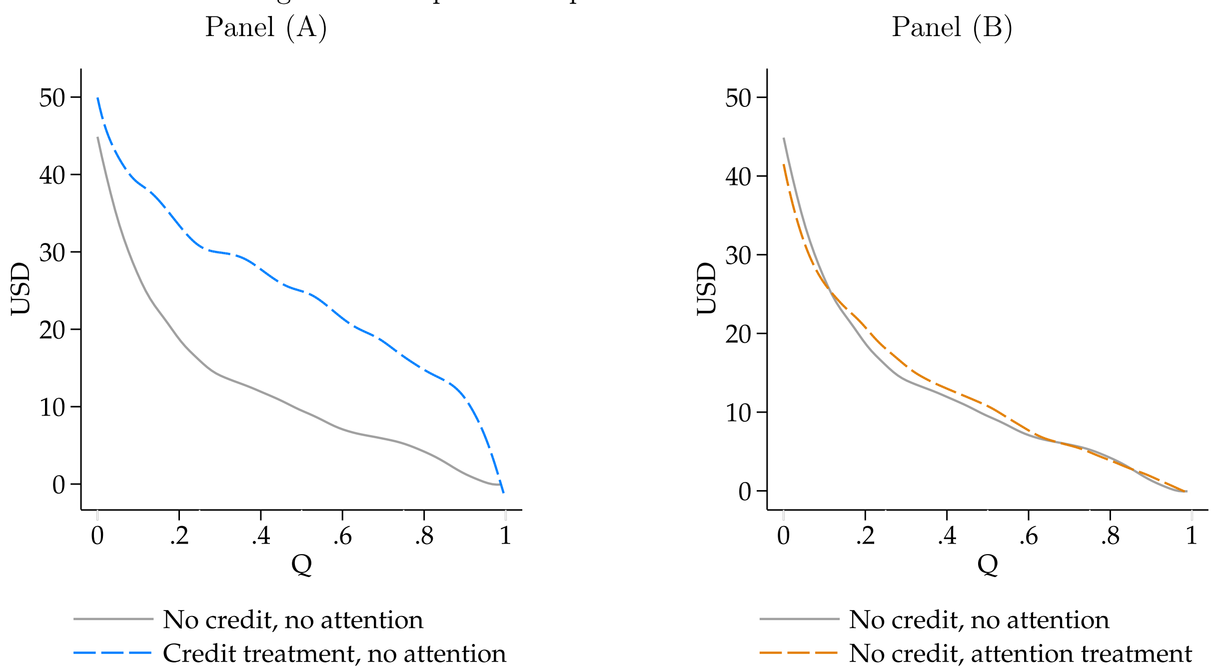
A Appendix Figures

Figure A1: Time use data: cooking hours by cooking technology



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

Figure A2: 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 experimental 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.

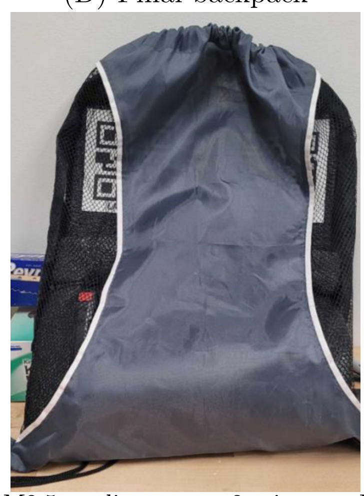
Figure A3: Devices to record air pollution and mesh backpacks containing them

(A) Particulate Matter

(B) Carbon Monoxide

(C) Backpack contents

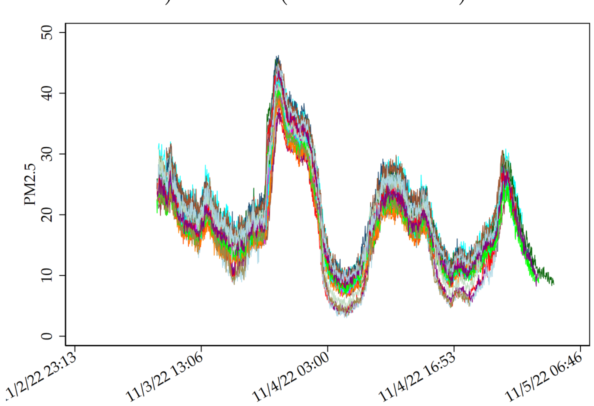
(D) Final backpack



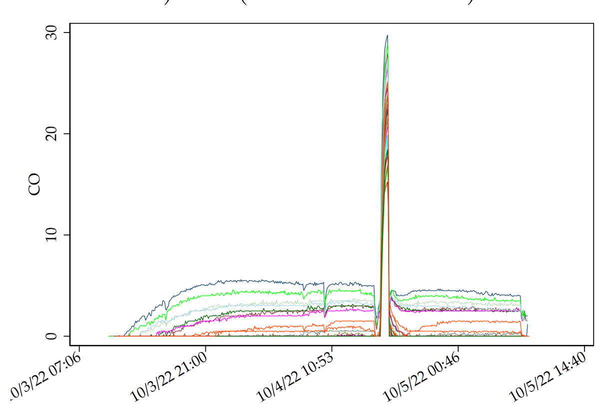
Panel A shows a Purple Air Inc. device, which records PM1.0 and PM2.5 readings every 2 minutes. Panel B shows a Lascar Electronics device, which records one CO reading every minute. Panel C displays how the devices are affixed to a lightweight foam material to stay in place. Behind the purple air device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

Figure A4: Co-located air pollution readings for devices

A) PM2.5 (PA-II devices)



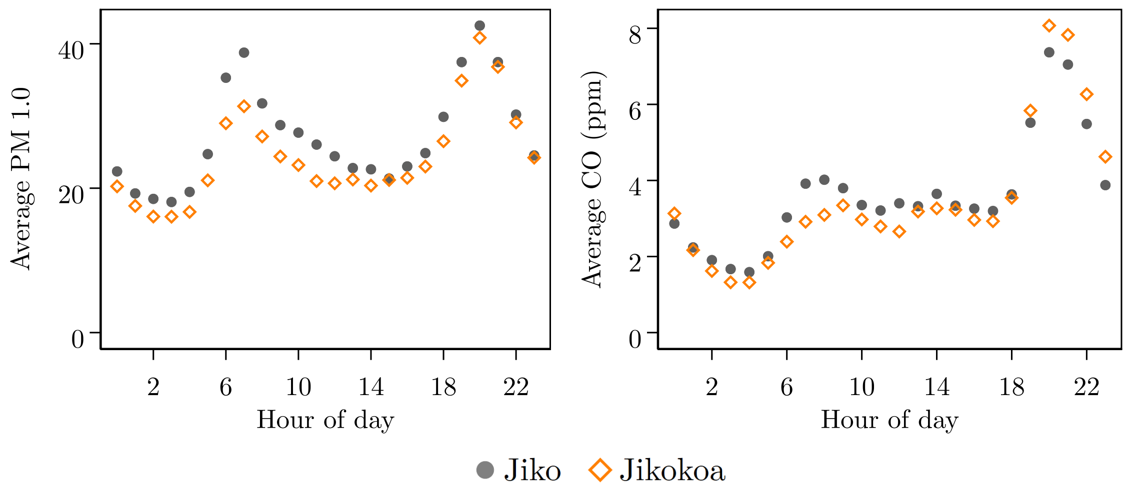
B) CO (LASCAR devices)



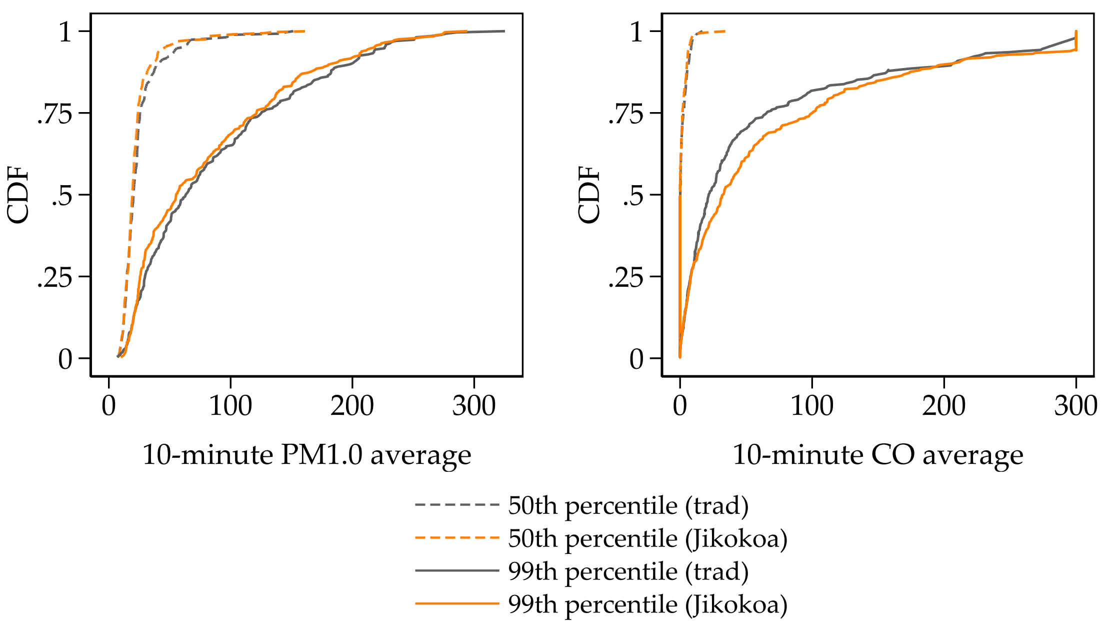
Air pollution data from a 48-hour testing window during which all 68 devices (34 PA-II devices and 34 LASCAR devices) were placed in the same location (Busara offices). To capture level differences across devices, all regressions include device fixed effects where relevant.

Figure A5: 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

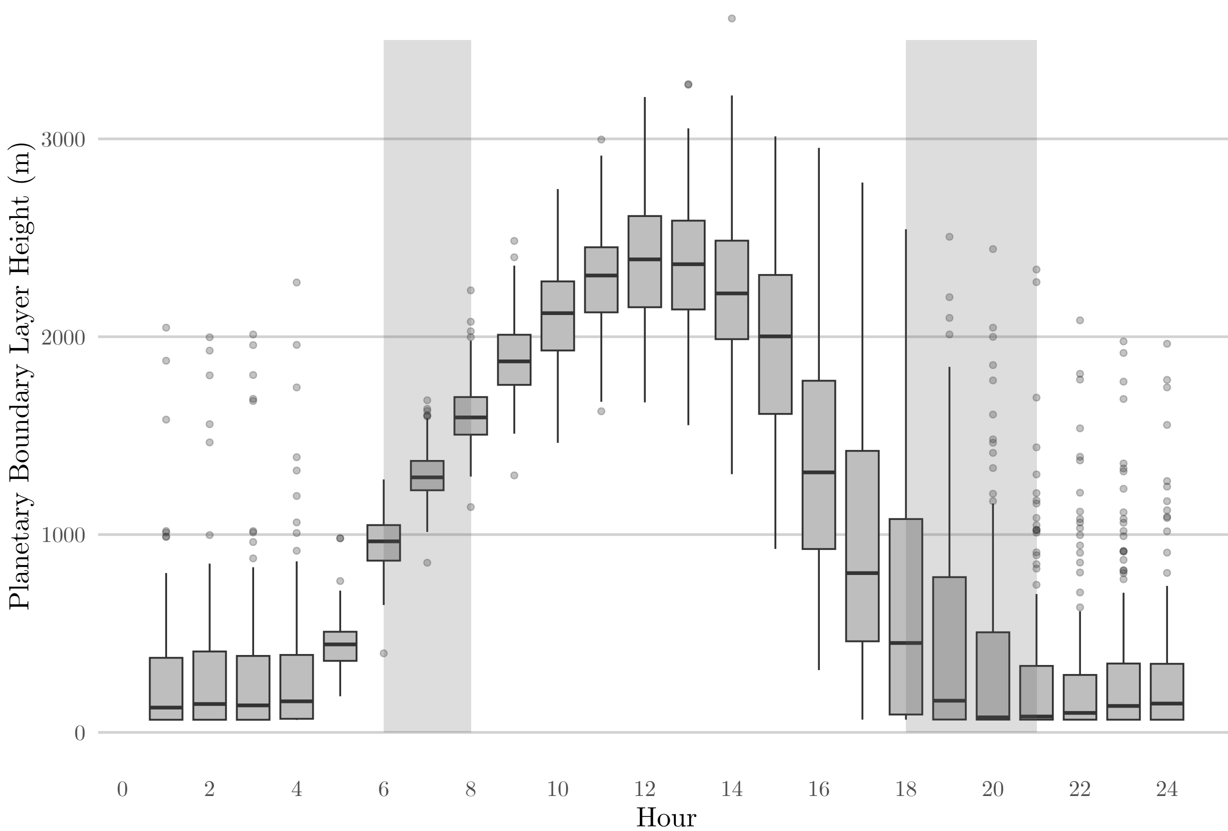


B) Distribution of 10th and 50th percentile of 10-minute concentrations, across individuals



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 4 presents the same for PM2.5.

Figure A6: Planetary boundary layer height using MERRA-2 satellite data



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

B Appendix Tables

Table A1: Experimental research on cookstove impacts

Authors	**Year**	**Country**	**Annualized IRR**
Berkouwer and Dean	2019	Kenya	294%
Allcott and Greenstone	2017	USA	-4%

Footnote here.

Table A2: 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, collected during the 2022–2023 endline survey. Hours add up to >24 because respondents occasionally report doing multiple activities in one hour. PM2.5 units are ug/m^3. CO units are ppm. Walking refers to walking outdoors, within or across neighborhoods. Schoolwork was typically done at home.

Table A3: First stage: impact of random treatments on take-up

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

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

Table A4: 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. Demographic and socioeconomic controls are the same as listed in Table 2. 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 A5: 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. The outcome variable for each row is hours spent on each task each day. Regressions control for the same demographic and socioeconomic controls as listed in Table 2. Rows add up to > 24 as some respondents report multiple activities within a given hour window.

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

Panel A) All

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

Panel B) When self-reporting cooking

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

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

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

Panel D) When self-reporting not cooking

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

Instrumental variables regressions where the randomly assigned price, credit treatment status, and their interaction are used as instruments for endline Jikokoa ownership. All PM2.5 regressions have 590 observations and a Weak IV F-statistic of 48. Observations vary across CO regressions because of the frequent occurrence of 0s. 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 use the same demographic and socioeconomic controls as listed in Table 2 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 A7: Causal impact of cookstove adoption on pollution exposure

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

	PM2.5				CO			
	(1) 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
N	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
N	651	651	651	651	656	656	656	656

Instrumental variables regression where the randomly assigned price, credit treatment status, and their interaction are used as instruments for endline Jikokoa ownership. All PM2.5 regressions have 590 observations and a Weak IV F-statistic of 48. All CO regressions have 607 observations and a Weak IV F-statistic of 49. 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 the same demographic and socioeconomic controls as listed in Table 2 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 A6 presents all four outcomes in logs.

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

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

Columns (2), (4), and (6) are each OLS regressions, while Columns (3), (5), and (7) are instrumental variables regressions which use randomly assigned price and credit treatment status as instruments for endline Jikokoa ownership. Standard errors clustered by respondent. All regressions include week of survey fixed effects, Lascar or PA-II device fixed effects, the interaction of and hour-of-day by day-of-week by neighborhood fixed effects, as well as the same demographic and socioeconomic controls listed in Table 2.

Table A9: 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 the same demographic and socioeconomic controls listed in Table 2 and fixed effects for the specific PA-II device used for that respondent.

Table A10: Pollution-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)	
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 control for the same demographic and socioeconomic controls as listed in Table 2.

Table A11: Non-pollution 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)	
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 control for the same demographic and socioeconomic controls as listed in Table 2.

Table A12: 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)	
Tuberculosis	0.01	0.02	702
	[0.08]	(0.01)	
COVID	0.01	-0.01	702
	[0.08]	(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)	
Diabetes	0.02	-0.00	702
	[0.14]	(0.02)	
Other	0.04	0.01	702
	[0.19]	(0.03)	

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 control for the same demographic and socioeconomic controls as listed in Table 2..

Table A13: 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 control for the same demographic and socioeconomic controls as listed in Table 2. See Section 3.4 and Appendix C for descriptions of the cognitive exercises conducted to measure cognitive function. Variables standardized for the control group to have mean 0 and standard deviation 1. Due to a technical issues with the tablets not displaying the behavioral games, the sample size for some of the cognition outcomes is smaller than in other outcome tables. Since this was a technical issue that occurred in the earlier stages of the surveying round, and since the order of follow-up surveys was randomized, it is unlikely that this biased the results in any meaningful way. Regressions control for baseline demographic and socioeconomic characteristics.

Table A14: Children's outcomes

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

Each row is an instrumental variables regression where the randomly assigned price, credit treatment status, and their interaction are used as instruments for endline Jikokoa ownership. Regressions control for the same demographic and socioeconomic controls as listed in Table 2. '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 A15: Children's outcomes for children age ≤ 5

	Control Mean	Treatment Effect	N
Child weight (kg)	14.16	-2.45	156
	[6.36]	(2.32)	
Child height (cm)	87.75	-2.79	131
	[30.02]	(6.98)	
Child arm circumference (cm)	15.64	2.25	152
	[8.73]	(2.61)	
Number of child health symptoms	1.22	0.34	327
	[1.51]	(0.40)	
Child health symptom index	0.02	0.29	327
	[1.01]	(0.30)	
Fever	0.18	-0.01	327
	[0.39]	(0.09)	
Vomiting	0.10	-0.02	327
	[0.30]	(0.06)	
Cough	0.41	0.03	327
	[0.49]	(0.12)	
Diarrhea	0.10	0.01	327
	[0.30]	(0.07)	
Breathlessness	0.04	0.09	327
	[0.20]	(0.06)	
Persistent headache	0.08	0.05	327
	[0.27]	(0.05)	
Very bad cough	0.25	0.11	327
	[0.44]	(0.09)	
Pneumonia - DHS	0.03	0.03	327
	[0.18]	(0.05)	
Pneumonia - WHO	0.17	0.02	327
	[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 control for the same demographic and socioeconomic controls as listed in Table 2. '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 A16: Heterogeneity in primary health impacts by baseline socioeconomic variables

	Treatment X Age	Treatment X WTP	Treatment X Health	Treatment X Health beliefs	N
	(1)	(2)	(3)	(4)	
Average systolic blood pressure	-0.73	-2.53	-2.20	-1.51	696
	(3.26)	(4.88)	(3.07)	(3.42)	
Average diastolic blood pressure	-2.49	-3.07	-3.77*	-1.58	696
	(2.09)	(3.13)	(1.97)	(2.32)	
Hypertension: Stage 1 or higher (>130/80)	-0.01	-0.05	-0.15*	-0.05	696
	(0.08)	(0.13)	(0.09)	(0.09)	
Hypertension: Stage 2 or higher (>140/90)	0.03	-0.20*	-0.15*	-0.09	696
	(0.08)	(0.12)	(0.08)	(0.08)	
Blood oxygen	0.05	0.94	-0.15	-0.05	696
	(0.33)	(0.60)	(0.35)	(0.37)	
Number of non-respiratory health symptoms	0.00	0.31	0.21	0.10	702
	(0.20)	(0.35)	(0.21)	(0.29)	
Non-respiratory health symptom index	-0.07	0.10	0.15	0.09	702
	(0.14)	(0.23)	(0.14)	(0.21)	
Number of respiratory health symptoms	0.25	0.04	-0.12	-0.02	702
	(0.20)	(0.34)	(0.21)	(0.24)	
Respiratory health symptom index	0.12	-0.06	-0.07	-0.00	702
	(0.12)	(0.19)	(0.11)	(0.13)	
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 control for the same demographic and socioeconomic controls as listed in Table 2. All heterogeneity variables are baseline measures and standardized to have mean 0 and standard deviation 1.

Table A17: Primary health outcomes by ambient concentrations

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

High ambient concentration is a dummy for above median average non-cooking PM2.5. Each row is an instrumental variables regression where the randomly assigned price, credit treatment status, and their interaction are used as instruments for endline Jikokoa ownership. Regressions control for the same demographic and socioeconomic controls as listed in Table 2. Table A10, Table A11, Table A12, and Table A13 present detailed results on the components of the symptoms, diagnoses, and cognitive indices, respectively.

Table A18: Primary health outcomes for rural respondents

	Control Mean (1)	Treatment Effect (2022 Ownership) (2)	Treatment Effect (2019 ownership) (3)	N
Average systolic blood pressure	126.36	8.35	7.38	53
	[17.33]	(5.57)	(5.74)	
Average diastolic blood pressure	81.17	15.35***	15.14***	53
	[10.47]	(3.19)	(3.75)	
Hypertension: Stage 1 or higher (>130/80)	0.59	0.49***	0.46**	53
	[0.50]	(0.16)	(0.18)	
Hypertension: Stage 2 or higher (>140/90)	0.23	0.44***	0.44**	53
	[0.43]	(0.17)	(0.18)	
Blood oxygen	96.95	-1.01*	-0.84*	53
	[1.65]	(0.52)	(0.51)	
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)	
Non-hospital health expenditures (USD)	4.13	2.75**	2.93***	53
	[6.64]	(1.17)	(1.07)	
Hospital visits in past 30 days	0.32	-0.08	-0.04	53
	[0.48]	(0.16)	(0.16)	
Hospital visit expenditures (USD)	4.36	18.02*	18.20*	53
	[15.50]	(9.39)	(10.09)	

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 control for the same demographic and socioeconomic controls as listed in Table 2.Table A10, Table A11, Table A12, and Table A13 present detailed results on the components of the symptoms, diagnoses, and cognitive indices, respectively. Table 4 presents results for the full sample.

Table A19: Testing for experimenter demand: direct effect of price on self-reported health

	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)

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 A20: 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 A21: 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 A22: Correlation between health and mean, median, maximum, and duration of CO exposure

	Mean SD	Mean Pollution (SD)	Median Pollution (SD)	Max Hourly Pollution (SD)	Hours Above 10coppm	N
	(1)	(2)	(3)	(4)	(5)	(6)
Average systolic blood pressure	123.49	1.50*	1.50	0.79	-0.08	645
	[21.60]	(0.88)	(1.02)	(0.88)	(0.27)	
Average diastolic blood pressure	81.74	1.32**	0.45	0.71	0.06	645
	[12.71]	(0.54)	(0.63)	(0.54)	(0.17)	
Blood oxygen	96.72	0.23**	0.20*	0.19*	0.06*	645
	[2.43]	(0.10)	(0.12)	(0.10)	(0.03)	
Number of health symptoms	2.52	0.14	0.14	0.17	0.08**	651
	[2.66]	(0.11)	(0.12)	(0.11)	(0.03)	
Health symptoms index (z-score)	-0.09	0.05	0.04	0.06*	0.03**	651
	[0.92]	(0.04)	(0.04)	(0.04)	(0.01)	
Number of non-respiratory health symptoms	0.96	0.05	0.05	0.11*	0.03*	651
	[1.44]	(0.06)	(0.07)	(0.06)	(0.02)	
Non-respiratory health symptom index	-0.07	0.04	0.02	0.08**	0.02*	651
	[0.99]	(0.04)	(0.05)	(0.04)	(0.01)	
Number of respiratory health symptoms	1.55	0.08	0.09	0.06	0.05**	651
	[1.60]	(0.06)	(0.07)	(0.06)	(0.02)	
Respiratory health symptom index	-0.09	0.06	0.05	0.03	0.02**	651
	[0.88]	(0.04)	(0.04)	(0.04)	(0.01)	
Number of health diagnoses	0.29	0.04*	0.02	0.03	0.00	651
	[0.56]	(0.02)	(0.03)	(0.02)	(0.01)	
Health diagnoses index	-0.04	0.04	0.03	0.04	-0.00	651
	[0.89]	(0.04)	(0.04)	(0.04)	(0.01)	

Each row and column cell in columns (2)–(5) is a separate OLS regression. All regressions control for the same baseline socioeconomic and demographic characteristics listed in Table 2. Table 5 provides the same for PM2.5.

Table A23: Correlation between health and average, maximum, and duration of PM2.5 exposure

	Mean SD	Average Pollution ()	Max Hourly Pollution ()		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. All regressions control for the same baseline socioeconomic and demographic characteristics listed in Table 2 as well as Lascar device fixed effects, month surveyed fixed effects, clustered geolocation fixed effects, and status as urban or rural. Regressions in columns (4) and (6) control for average PM2.5 pollution, while regressions in columns (3) and (5) don't. Table A10, Table A11 and Table A12 present detailed results on symptoms and diagnoses.

Table A24: Correlation between health and mean, median, maximum, and duration of PM2.5 exposure (among non-adopters)

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

Each row and column cell in columns (2)–(5) is a separate OLS regression. All regressions control for the same baseline socioeconomic and demographic characteristics listed in Table 2 as well as PA-II device fixed effects, month surveyed fixed effects, clustered geolocation fixed effects, and status as urban or rural. Hypertension refers to stage 1. Table 5 present the same for the entire sample.

Table A25: Correlation between health and mean, median, maximum, and duration of PM2.5 exposure (among adopters)

	Mean SD	Mean Pollution (SD)	Median Pollution (SD)	Max Hourly Pollution (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. All regressions control for the same baseline socioeconomic and demographic characteristics listed in Table 2 as well as PA-II device fixed effects, month surveyed fixed effects, clustered geolocation fixed effects, and status as urban or rural. Hypertension refers to stage 1. Table 5 present the same for the entire sample.

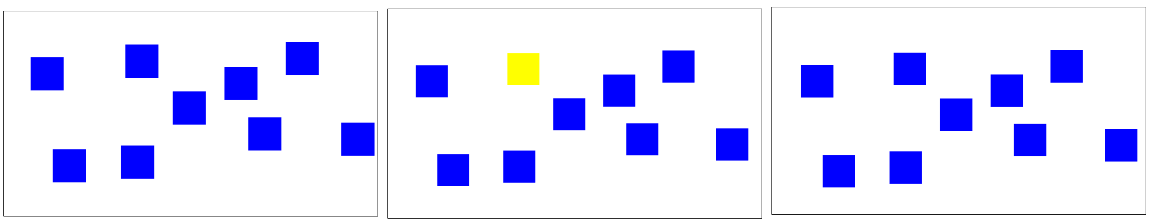
C Cognitive assessments

C.1 Reverse Corsi Block

Implementation of the Reverse Corsi Block task follows Brunetti, Del Gatto, and Delogu (2014). For each trial, nine blue blocks appear in random locations on the screen. They take turns lighting up. Respondents are then asked to tap the blocks in reverse order of how they lit up (see Figure A7). 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 A7: Corsi Stimuli

(a) Blocks appear in random positions — (b) Blocks light up yellow randomly — (c) Respondents tap blocks in reverse order



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

C.2 Hearts and Flowers

Implementation of the Hearts and Flowers task follows the “dots" task outlined by Davidson et al. (2006). Respondents see a fixation dot in the center of their screen with blue boxes on the left and right. Respondents then see a sequence of hearts and flowers appear on the boxes. For each trial, respondents must press either the “Q" or “P" key. When a heart appears, respondents must press the key on the same side as the heart. While when a flower appears, respondents must press the key on the opposite side (see Figure A8).

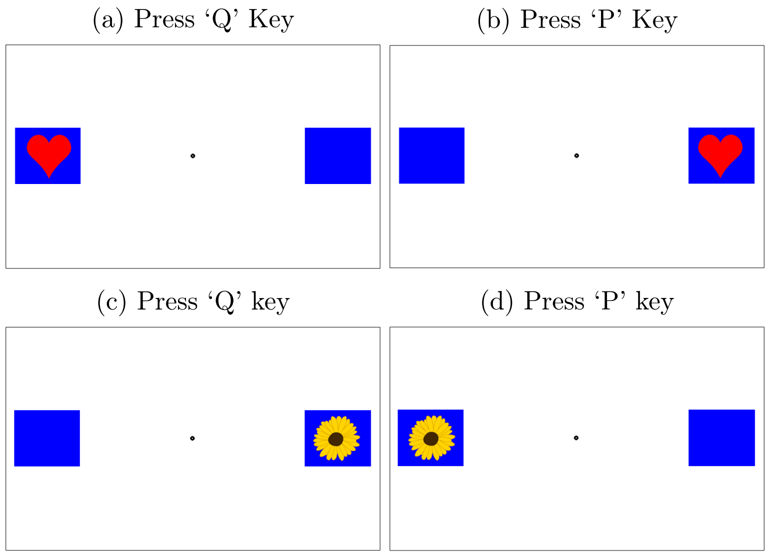


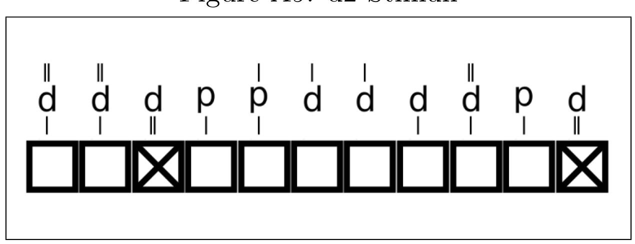
Figure A8: Hearts and Flowers Possible Stimuli and Responses

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

C.3 d2 Attention Task

The d2 task follows the general instructions outlined in Bates and Lemay Jr. (2004) and Brickenkamp and Zillmer (1998). For each trial, eleven letters (either p or d) appear on the screen with between zero and two dashes above and zero and two dashes below for a total number of dashes between zero and four (see Figure A9). 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 A9: 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.