



## **ADBI Working Paper Series**

### **HIGH INDOOR AIR POLLUTION IN A DEVELOPING MEGACITY: THE ROLE OF OUTDOOR PM<sub>2.5</sub> AND HOUSEHOLD CHARACTERISTICS**

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**Abstract**

Exposure to fine particulate matter ( $PM_{2.5}$ ) poses major health risks, especially in rapidly urbanizing cities. As urbanization accelerates, people in low- and middle-income countries spend more time indoors, where pollution risks remain poorly understood. We present evidence from over 152,000 monitor-hours of indoor  $PM_{2.5}$  measurements across homes in Jakarta, Indonesia, one of the world's largest and most polluted cities. We find that mean daily indoor and outdoor  $PM_{2.5}$  levels are both dangerously high, eight times above World Health Organization's (WHO) health-based guidelines. In addition, indoor  $PM_{2.5}$  frequently reach hazardous levels—40 to 100 times the WHO guideline, levels that outdoor monitors do not capture. Unlike in developed settings, most indoor pollution originates from outdoor infiltration. Survey data also reveal large inequalities: lower-income households experience double the mean indoor  $PM_{2.5}$  of higher-income households. Our findings show that indoor air pollution remains both severe and unequally distributed, even in this population where most people have adopted cleaner cooking fuels. Researchers and policymakers should integrate outdoor air quality mapping with demographically representative indoor monitoring to close key data gaps, enabling more accurate exposure estimates and better-targeted environmental health policies.

**Keywords:** indoor air pollution level, air pollution infiltration, Indonesia

**JEL Classification:** O13, Q53

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# 1. INTRODUCTION

Fine particulate matter ( $PM_{2.5}$ ) is the world's leading environmental risk factor to human health (Health Effects Institute 2024). In 2018, among the 7.3 billion people directly exposed to unsafe average annual  $PM_{2.5}$  concentrations globally, 80% lived in low- and middle-income countries (Rentschler and Leonova 2023). Rapidly growing cities face especially hazardous levels of ambient air pollution, fueled by intensive use of fossil fuels, industrialization, construction, and congestion (Manisalidis et al. 2020). This pollution burden is expected to intensify: by 2050, an estimated 68% of the global population will reside in cities, nearly 90% of this growth being concentrated in Asia and Africa.

Even though World Development Indicators estimated that 3.45 billion people in low- and middle-income countries currently live in urban areas, we know surprisingly little about their patterns of air pollution exposure.<sup>1</sup> Most existing studies focus on rural households, where indoor pollution is primarily driven by the use of solid fuels for cooking. For instance, the Global Burden of Disease (GBD) models household air pollution based on the proportion of the population using solid fuels for cooking (GBD 2021 HAP Global Collaborators 2025). This approach underscores a broader knowledge gap: a limited understanding of indoor pollution sources and exposure in rapidly urbanizing environments.

This knowledge gap is fundamentally a data gap. While outdoor air pollution data are limited, indoor air quality data are even scarcer, as very few households own indoor monitors and those that do are typically wealthier and unrepresentative of the broader population. We address this critical shortfall by collecting real-time measurements of both indoor and outdoor  $PM_{2.5}$  in Jakarta, Indonesia, one of the world's largest and most polluted megacities, where traffic, industry, and dense residential activity sustain persistently unhealthy air. We equip 308 urban households with indoor air quality monitors, capturing over 152,000 monitor-hours of indoor  $PM_{2.5}$  data. Importantly, these monitors did not display  $PM_{2.5}$  levels, so the monitors themselves did not induce differential behaviors. We complement these with outdoor  $PM_{2.5}$  readings from 63 low-cost sensors, dramatically improving spatial granularity compared to the two reference-grade monitors previously available. Detailed household surveys further document demographic, behavioral, and housing characteristics. To our knowledge, this is one of the largest studies of indoor air pollution among urban residents in low- and middle-income countries.

Using this rich dataset, we (1) characterize the relationship between indoor and outdoor  $PM_{2.5}$  concentrations; (2) estimate infiltration rates of outdoor pollution into homes; (3) quantify the contribution of hyperlocal sources such as smoking and neighborhood waste burning; and (4) examine how indoor exposure varies across income levels. Our household surveys provide essential context for interpreting these measurements. Firstly, respondents—primarily women—report spending approximately 80% of their time at home, and their school-aged children spend about 70% of their time indoors, making the home environment a critical exposure setting. Secondly, 98% of households report using liquefied petroleum gas (LPG) for cooking, reflecting substantial progress toward Sustainable Development Goal targets for clean cooking access. This context allows us to examine the persistence of indoor pollution even after a successful clean cooking fuel transition.

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<sup>1</sup> World Bank Group. Urban Population – Low and Middle Income. <https://data.worldbank.org/indicator/SP.URB.TOTL?locations=XO>.

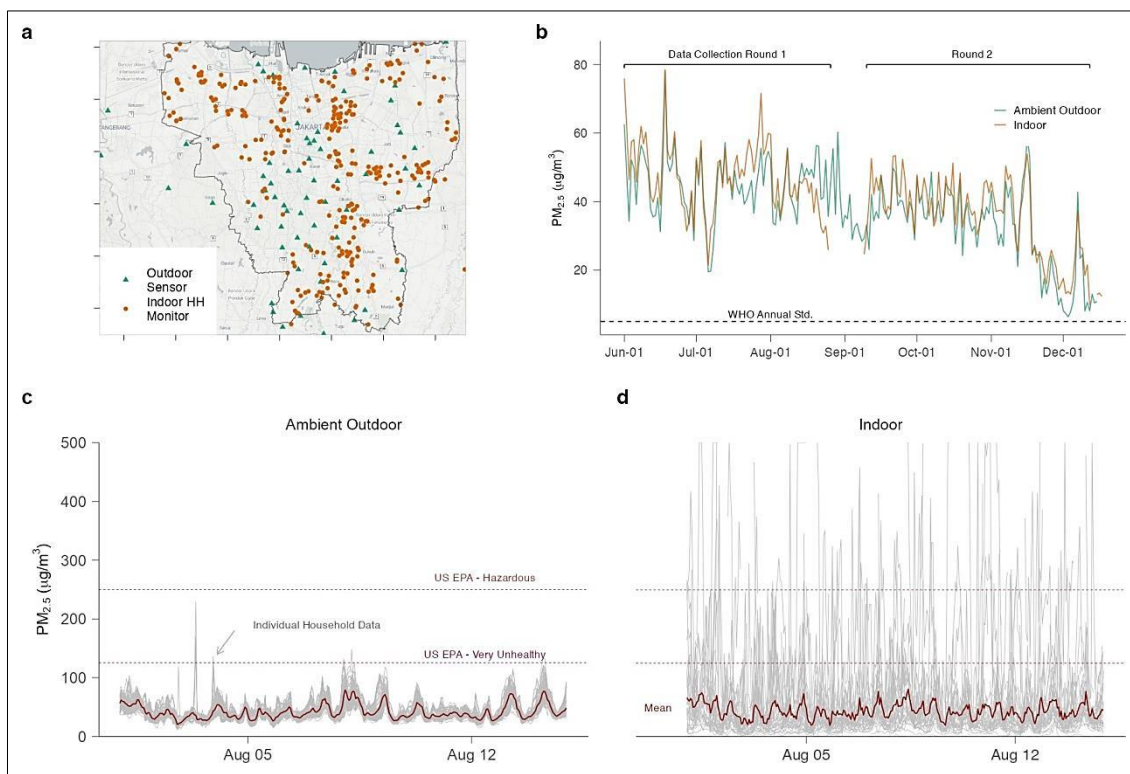
## 2. RESULTS

### 2.1 High Indoor $PM_{2.5}$ Levels

Our main finding is that average indoor  $PM_{2.5}$  concentrations closely map outdoor  $PM_{2.5}$  ambient concentrations on average, but episodic spikes of indoor  $PM_{2.5}$  are often much higher than those of outdoor  $PM_{2.5}$ . Overall, this implies that households in Jakarta are on average exposed to higher levels of  $PM_{2.5}$  indoors than outdoors.

We first establish that both indoor and outdoor  $PM_{2.5}$  levels are at unhealthy levels. During our study period, the mean indoor daily  $PM_{2.5}$  concentration was  $40.7 \mu\text{g}/\text{m}^3$ , while the mean outdoor daily  $PM_{2.5}$  concentration was  $37.8 \mu\text{g}/\text{m}^3$ . Both levels were about eight times higher than the World Health Organization (WHO) annual standard of  $5 \mu\text{g}/\text{m}^3$ , as shown in Figure 1.

**Figure 1: Indoor and Outdoor  $PM_{2.5}$  in Jakarta**



Notes: **(a)** Locations of respondents and installed air quality monitoring hardware. There are 308 indoor air quality monitors (orange) installed in respondent homes, and 63 low-cost sensors (green) to measure respondent-specific outdoor air quality. **(b)** Daily average outdoor and indoor pollution levels in Jakarta. To account for the uneven spatial distribution of outdoor sensors, we first computed district-level averages for outdoor readings, which were then aggregated to produce a daily citywide average. Indoor pollution levels were averaged across all households on a daily basis. The gap in the indoor data from 26 August to 8 September occurred during a transition period when the air quality hardware was being moved between households. **(c)** Hourly outdoor  $PM_{2.5}$  from 1–14 August 2022. Gray lines show hourly  $PM_{2.5}$  concentrations for each individual low-cost sensor, while the maroon line shows the mean concentration across all 68 sensors. **(d)** Analogous to (c), this plot shows hourly indoor  $PM_{2.5}$ .

In addition to persistently high pollution levels, we find that indoor spaces experience severe episodic pollution events. Figure 1d displays hourly indoor pollution levels at the individual household level for a representative two-week period from our sample. The figure shows frequent spikes in indoor pollution, soaring far beyond levels

characterized as hazardous by the United States Environmental Protection Agency (US EPA) and surpassing thresholds typically associated with emergency conditions. On average, indoor air exceeds the US EPA's "very unhealthy" threshold 4% of the time, at levels that are rarely observed in the outdoor measurements.

In our accompanying survey, we find that respondents, 90% of whom were women, reported spending 80% of their time at home. We focused on parents of elementary school children, who reported that their children spent an average of 70% of their time indoors. Thus indoor pollution levels are highly representative of overall  $PM_{2.5}$  exposure for women and children in our study population. Importantly, the sample targets low- and middle-income households, offering rare insights into a population largely overlooked in existing research on indoor air quality. Existing research on indoor pollution predominantly examines households in high-income countries (Burke et al. 2022; Krebs et al. 2021; Lunderberg et al. 2023) or relies on small samples observed over short periods of time (Lim et al. 2022), leaving significant gaps in our understanding of indoor air pollution exposure in developing urban settings. More details on our sampling approach can be found in Section 4.1.

Overall, these findings show that while outdoor levels capture average indoor exposure, they fail to account for the pollution burden from episodic indoor spikes. Individuals with similar average exposures may experience very different intensities and frequencies of severe pollution events, patterns that are missed when relying solely on outdoor pollution data. The health impacts of repeated short-term spikes remain poorly understood, underscoring the need for research that considers pollution spikes, not just mean levels.

## 2.2 Outdoor Infiltration into Indoor Spaces

We model how ambient outdoor  $PM_{2.5}$  infiltrates into indoor spaces; this decomposes the contributions of ambient outdoor sources versus hyperlocal sources to indoor pollution. Ambient outdoor pollution refers to background  $PM_{2.5}$  concentrations measured by our citywide sensor network, while hyperlocal sources—including smoking and neighborhood burning—occur at spatial scales too fine for our outdoor sensors to capture.

We estimate that a  $1 \mu\text{g}/\text{m}^3$  increase in  $PM_{2.5}$  is associated with a .689 (95% CI, 0.508, 0.871;  $P < 0.001$ )  $\mu\text{g}/\text{m}^3$  increase in indoor  $PM_{2.5}$  in the same hour. This rate is about 2.5 times the rate typically estimated in the United States (Lunderberg et al. 2023), implying that in low- and middle- income countries, indoor spaces do not offer the same protection from outdoor pollution as in high-income countries. In addition, we find that infiltration happens much more quickly than in high-income settings. We estimate that all infiltration happens within the hour, as opposed to estimated lagged effects of up to six hours in high-income settings (Burke et al. 2022; Lunderberg et al. 2023). These estimates are robust to alternative regression models, as seen in Figure 2a.

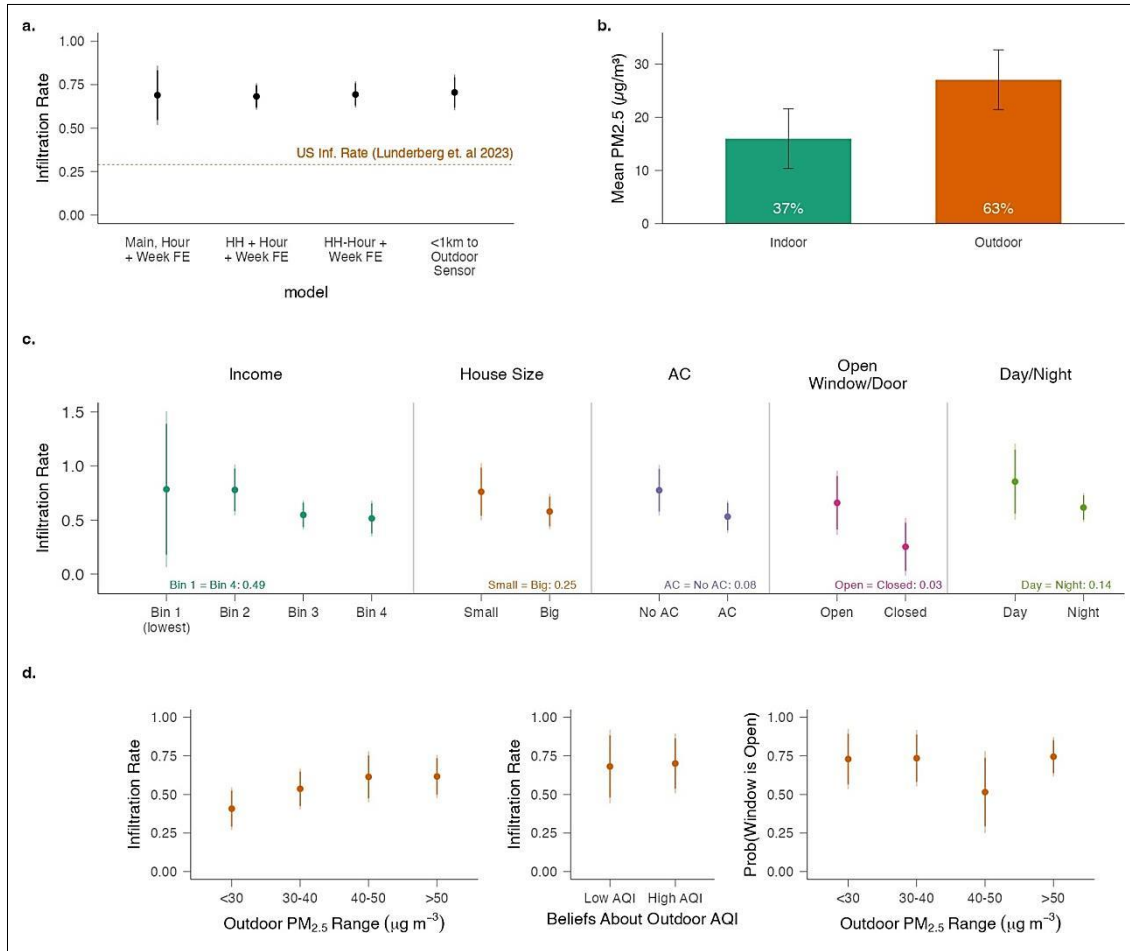
With these high infiltration rates, most indoor air pollution in Jakarta originates from the outdoors—unlike in high-income countries, where indoor pollution typically stems from indoor sources (Metcalf and Roth 2025). We estimate that 63% of mean indoor  $PM_{2.5}$  comes from ambient outdoor pollution (Figure 2b).

To shed light on the causes behind these high infiltration rates, we examine heterogeneity in infiltration rates in Figure 2c. We find statistically significant differences based on air conditioning (AC) ownership ( $p = 0.08$ ) and whether the monitor room has an open versus closed window or door ( $p = 0.03$ ). These findings corroborate ventilation as a key determinant of infiltration rates. In Jakarta's hot and humid climate,

households without AC often rely on natural ventilation, increasing their exposure to outdoor pollution.

Our results suggest that differences in infiltration rates are driven by long-term household characteristics. This contrasts with previous studies in high-income settings that find that infiltration rates are primarily driven by short-term behavioral adjustments (Baquie et al. 2024; Burke et al. 2022). We use three analyses to show that households are not actively taking short-term actions to reduce infiltration.

**Figure 2: Infiltration Rate from Ambient Outdoor to Inside Homes**



Notes: **(a)** Infiltration rates, defined by the regression of indoor  $PM_{2.5}$  on outdoor  $PM_{2.5}$ . Each point corresponds to a different regression specification. The first specification controls for hour-of-day and week fixed effects, the second adds household fixed effects, and the third further restricts the sample to households located within 1 km of an outdoor sensor. All regressions control for outdoor temperature and humidity. **(b)** Decomposition of  $PM_{2.5}$  sources into ambient outdoor and hyperlocal contributions. The ambient outdoor contribution is calculated by multiplying infiltration rates (from the main regression specification in panel a) by the mean outdoor  $PM_{2.5}$ . The hyperlocal source is computed by subtracting the outdoor contribution from the total measured indoor  $PM_{2.5}$ . Error bars reflect standard errors based on infiltration rates and are scaled by the mean  $PM_{2.5}$  for each quartile; thus the breakdown should be interpreted as the source contribution conditional on the mean  $PM_{2.5}$ . **(c)** Heterogeneity in infiltration rates by household and behavioral characteristics, including income quartile, number of rooms in the house (including bathrooms), air conditioning (AC) presence, whether a window/door was open in the room, and time of day (day/night). P-values for tests of equality between coefficients are shown in the respective graphs. **(d)** Household behavior in response to outdoor pollution levels. The first panel shows heterogeneity in the infiltration rate as a function of outdoor  $PM_{2.5}$  concentrations. The second panel shows heterogeneity in infiltration rates based on households' beliefs about outdoor air quality, comparing those who perceive it as generally unhealthy (high AQI) versus those who do not (low AQI). The third panel regresses the probability of opening windows or doors on outdoor levels. Points represent mean estimates; darker error bars show 90% confidence intervals and lighter error bars show 95% confidence intervals. Errors are clustered at the household level.

Firstly, previous literature has found that infiltration rates decline at high outdoor  $PM_{2.5}$  concentrations, suggesting that people actively modify their behavior to limit exposure at higher levels of outdoor pollution (Burke et al. 2022; Lunderberg et al. 2023). However, we do not find this relationship here. In fact, infiltration increases at higher  $PM_{2.5}$  concentrations. This pattern, shown in Figure 2d, could be driven by several factors, including concentration gradients between outdoor and indoor pollution, meteorological conditions correlated with outdoor pollution levels, or the presence of high-emission hyperlocal pollution sources (Lunderberg et al. 2023; MacNeill et al. 2012).

Secondly, we find that households who believe the outdoor air quality is unhealthy have analogous infiltration rates to those who believe the outdoor air quality is relatively healthy. Households were classified based on whether they generally thought outdoor air pollution was unhealthy (high vs. low Air Quality Index). As shown in Figure 2d, infiltration rates do not differ based on this belief, suggesting that differential beliefs are not translating into differential protective actions.

Finally, we assess whether ventilation behaviors (e.g., opening windows or doors) respond to outdoor pollution levels. If households actively manage infiltration, we expect them to close windows when pollution is high. However, Figure 2d shows no relationship between window or door openness and outdoor pollution levels. While opening or closing windows is a short-term behavior that can, in theory, be adapted, it is difficult to expect households to keep windows closed in a hot and humid climate like Jakarta, where natural ventilation is necessary for cooling.

## 2.3 Hyperlocal Sources of Indoor $PM_{2.5}$ Spikes

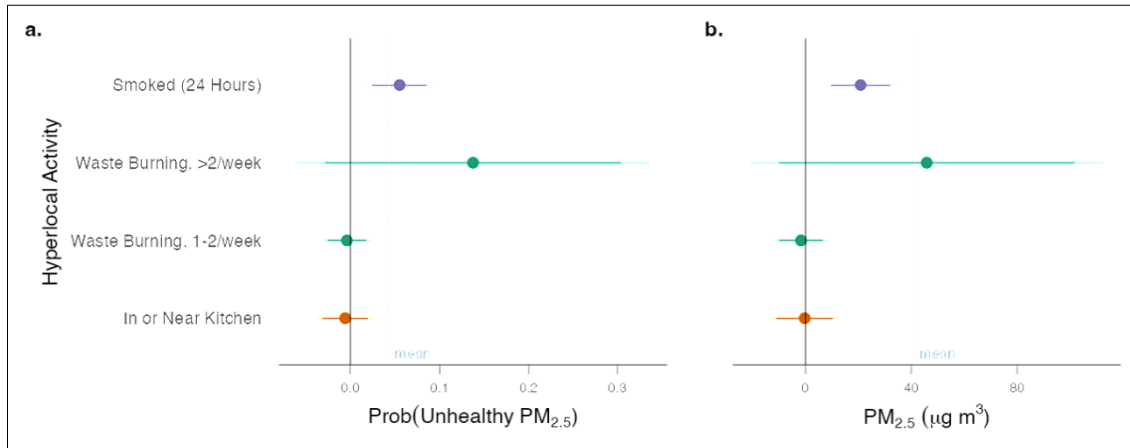
While ambient outdoor pollution is the primary driver of persistently high indoor  $PM_{2.5}$  concentrations, hyperlocal sources are responsible for the episodic spikes that lead to extreme pollution levels. As shown in Figure 3, our survey clearly documents the impact of two major sources: indoor smoking and neighborhood waste burning.<sup>2</sup>

We find that households who reported indoor smoking within the last 24 hours experienced significantly higher indoor pollution levels. These households had a 5.51% (95% CI: 1.85–9.17,  $P < 0.001$ ) greater probability of pollution spikes reaching very unhealthy levels. Given that the sample average probability of pollution spikes is 4.43%, this translates to a 127% increase. Analogously, smoking was associated with 20.8  $\mu g/m^3$  (95% CI: 7.36–34.3,  $P < 0.001$ ) higher average hourly indoor  $PM_{2.5}$  concentrations, a 50% increase compared to the sample mean.

Neighborhood-level waste burning is another significant source of indoor air pollution in Jakarta. Households in areas with more than two waste-burning events per week saw notably higher indoor  $PM_{2.5}$  concentrations. However, accurately quantifying the effect of burning events on indoor pollution is challenging, as we rely on self-reported data and some events may be misreported. These measurement limitations contribute to wide confidence intervals around our estimated effects.

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<sup>2</sup> It is worth noting that another major contributor to indoor air pollution that has been documented extensively is the combustion of solid fuels and kerosene for cooking. However, in Indonesia, the widespread adoption of LPG cookstoves has largely eliminated variation in cooking fuel use (Astuti, Day, and Emery 2019); in our survey, 98% of households reported using LPG cookstoves for cooking. While LPG cookstoves still generate large spikes in pollution, our data do not include detailed information on cooking activities, preventing us from drawing insights into this source of indoor pollution.

**Figure 3: Contributions of Hyperlocal Pollution**

Notes: **(a)** Regression coefficients for the probability that  $PM_{2.5}$  exceeds the EPA's AQI threshold for very unhealthy levels (greater than  $125 \mu g/m^3$ ) as a function of indoor pollution-generating activities: (1) whether the monitor is in or near the kitchen; (2) whether the household reported observing one or two waste burning events in the neighborhood in the seven days preceding the interview; (3) whether the household reported observing more than two waste burning events in the neighborhood in the seven days preceding the interview; and (4) whether the household reported any smoking indoors in the 24 hours preceding the interview. **(b)** Analogous to panel (a), this panel shows regression coefficients of indoor  $PM_{2.5}$  concentrations on indoor pollution-generating activities. Points represent mean estimates; darker error bars show 90% confidence intervals and lighter error bars show 95% confidence intervals. Errors are clustered at the household level. The light blue dashed line shows the sample mean for each respective measure of indoor pollution.

In addition to smoking and neighborhood waste burning, there are likely other hyperlocal pollution sources contributing to the observed spikes in indoor air pollution. Such activities may include cooking, traffic emissions, industrial operations, and commercial activities. An exhaustive list of all polluting activities is beyond the scope of our analysis.

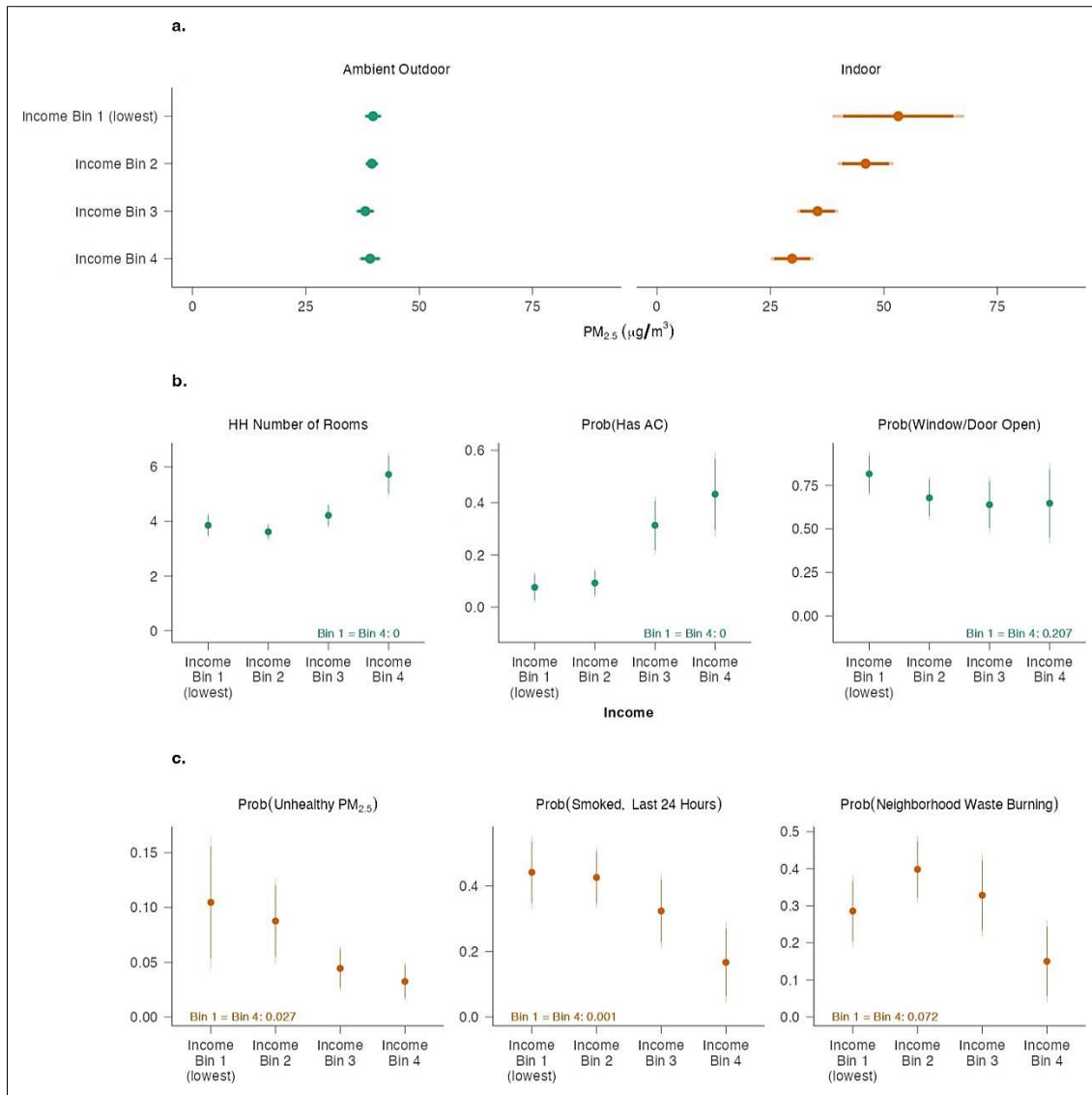
## 2.4 Heterogeneity by Income

Households across the income distribution experience similar levels of ambient outdoor pollution exposure, but lower-income households suffer higher levels of indoor  $PM_{2.5}$ . As shown in Figure 4a, moving from the highest to the lowest income quartile in our sample corresponds to an increase of  $23.4 \mu g/m^3$  in mean  $PM_{2.5}$ , representing a 79% increase. This finding is consistent across various aggregation techniques used to calculate the mean (Appendix Figure A2).

Indoor air quality is determined by how much outdoor  $PM_{2.5}$  infiltrates indoors and how much pollution is generated hyperlocally. We find that income affects both these factors. Through its impact on housing quality and ventilation choices, income may affect the infiltration of outdoor pollution into indoor spaces (Lunderberg et al. 2023). In Jakarta's hot and humid climate, households may cool indoor spaces through either AC or natural ventilation. As shown in Figure 4b, higher-income households are significantly more likely to have AC, reducing their reliance on open windows or doors for ventilation. Consistent with this pattern, households in the lowest income quartile were more likely to keep windows or doors open in the air quality monitor room at the time of surveying, although this difference is not statistically significant. Higher-income households also tend to live in larger homes, potentially enabling them to separate living areas from cooking and smoking areas, for example. Taken together, these patterns indicate that lower-income households tend to have lower housing quality

and face greater difficulties in regulating indoor temperatures, making them more vulnerable to outdoor pollution infiltration, as discussed in Section 2.2.

**Figure 4: Indoor  $PM_{2.5}$  Higher for Lower-income Households**



Notes: **(a)** Mean  $PM_{2.5}$  concentrations across income quartiles for indoor and ambient outdoor measurements. For ambient outdoor measurements, a household-hour level weighted average was calculated using air quality readings from the three nearest sensors, with weights inversely proportional to distance. A mean level was then computed for each household, followed by aggregation across households within each income quartile. Indoor  $PM_{2.5}$  measurements were aggregated similarly, starting with household-level means and then averaging across households within each income quartile. **(b)** Regressions of household characteristics related to outdoor infiltration by income quartile, with Income Bin 1 as the lowest income. Panels show regression coefficients where the outcome variable is the number of rooms, whether the household has air conditioning, and whether windows/doors were open when surveyed. **(c)** Similar to **(b)**, regressions of characteristics linked to hyperlocal pollution sources on income quartile. The first panel is the probability that hourly  $PM_{2.5}$  exceeds the EPA's AQI threshold for very unhealthy levels (greater than  $125 \mu g/m^3$ ) according to income quartile, controlling for outdoor pollution, temperature, humidity, week, and hour-of-day fixed effects. Income Bin 1 (lowest income) is the reference group. The second panel regresses indoor smoking in the last 24 hours on income quartile. The third panel regresses whether there were more than two waste burning activities reported that week in the neighborhood on income quartile. Points represent mean estimates; darker error bars show 90% confidence intervals and lighter error bars show 95% confidence intervals. Standard errors are clustered at the household level.

Income is also closely linked to hyperlocal pollution sources shaped by household and neighborhood behaviors. We proxy for exposure to hyperlocal sources with the likelihood that mean hourly  $PM_{2.5}$  exceeds the EPA's AQI threshold for very unhealthy levels ( $125 \mu\text{g}/\text{m}^3$ ). Since ambient outdoor pollution rarely reaches such extreme levels in Jakarta, these spikes likely result from episodic emissions occurring inside or near the home. As shown in Figure 4c, households in the lowest income quartile experience unhealthy pollution spikes 10.5% of the time, compared to just 3.23% in the highest income quartile. A statistical test of the difference in coefficients between the lowest income quartile and the highest quartile confirms that this difference is statistically significant ( $p = 0.027$ ). This disparity suggests a greater burden of episodic pollution for low-income households.

We also examine two prominent hyperlocal pollution sources—indoor smoking and neighborhood waste burning—and their relationship with income. Indoor smoking is significantly less common in higher-income households, as shown in Figure 4c. Waste burning, another potential contributor, does not follow a clear income gradient, though measurement challenges limit the robustness of this finding.<sup>3</sup>

### 3. DISCUSSION

We show that indoor  $PM_{2.5}$  exposure in Jakarta is both persistently high and unequally distributed across income groups. In addition to elevated mean levels, indoor environments frequently experience hazardous pollution spikes, extremes not captured by outdoor monitors. These spikes occur despite 98% of households in our sample using LPG cookstoves, which are typically considered clean cooking. This suggests that addressing indoor air pollution in low- and middle-income countries requires a broader framework than is currently used. For example, the GBD framework defines household air pollution in terms of solid fuel use, a metric that has guided policy and resource allocation globally. However, this definition may not fully capture the indoor pollution risks experienced by urban populations using cleaner fuels but still exposed to high ambient and infiltrated pollution.

We find that most indoor pollution stems from outdoor  $PM_{2.5}$  infiltration, with an infiltration factor (0.689) substantially higher than estimates in high-income countries. These high rates are related to structural characteristics, such as the absence of AC and the dependence on natural ventilation, rather than short-term behavioral responses. While information campaigns may increase awareness of infiltration risks, economic and infrastructural constraints likely limit behavioral adjustments. Mitigation efforts must therefore prioritize pollution controls at the source, targeting major contributors like vehicular traffic and industrial emissions. In the interim, coupling outdoor air quality mapping with demographically representative indoor measurements can help better characterize true exposure and inform more equitable policy design.

In contrast, episodic peaks in indoor pollution are driven by hyperlocal sources such as indoor smoking and neighborhood waste burning, activities more amenable to individual or local intervention. Information campaigns and stronger enforcement

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<sup>3</sup>As previously mentioned, the combustion of solid fuels and kerosene for cooking has previously been documented as another major contribution to indoor air pollution. However, the widespread adoption of LPG cookstoves has largely eliminated variation in cooking fuel use and the absence of details on cooking activities in our data prevent us from further investigating the role of cooking in air pollution.

against garbage burning could reduce these extreme events and their associated health risks.

Our findings also have important distributional implications. Consistent with previous studies (Burke et al. 2022; Greenstone, Lee, and Sahai 2021; Ito and Zhang 2020), we show that low-income households are exposed to the highest levels of indoor air pollution. Relying solely on outdoor air quality as a proxy for exposure may systematically underestimate both overall exposure and disparities across income groups. These inequalities stem from both higher infiltration rates, associated with poorer housing conditions, and greater hyperlocal emissions.

Finally, while our study provides novel insights into indoor  $PM_{2.5}$  exposure in a developing urban setting, it has several limitations. Firstly, our sample focuses on households with elementary school-aged children, and therefore is not fully representative of Jakarta's population. Future research should assess whether similar patterns hold for other demographic groups, particularly groups with heightened health risks, such as the elderly or those with pre-existing health conditions. Secondly, while we identify key determinants of indoor air quality, we do not capture all possible hyperlocal pollution sources, such as cooking emissions, incense burning, or traffic-related infiltration; nor are we able to track personal exposure outside the home. Relatedly, our reliance on stationary indoor monitors limits our ability to account for variations in individual exposure, as people move between environments. Expanding real-time monitoring to include wearable sensors and more detailed measurements of indoor pollution sources could provide a fuller picture of exposure risks.

## 4. METHODS

High levels of outdoor air pollution are sustained in Jakarta throughout the whole year, and historically especially high between the months of May and October. We design the study to cover this high pollution season and conduct it in two successive rounds, with approximately 154 households participating in each round. Round 1 was conducted from 1 June to 28 August 2024. Round 2 was conducted from 10 September to 10 December 2024. This randomized controlled trial was registered on the AEA RCT registry (Identification No. AEARCTR-0013110) and received IRB approval from the University of Chicago (Protocol No. IRB23-0310) and from Badan Riset Dan Inovasi Nasional (Application No. 29012024000032). Individual respondents consented to the collection of the indoor air quality data and survey data used in this study. Ambient outdoor  $PM_{2.5}$  data come from devices monitored by our hardware implementation partner, not associated with private individuals, and therefore without personally identifying information.

### 4.1 Study Participants and Datasets

**Study participants.** Households participating in our study were selected to cover households in Jakarta. We selected our sample by partnering with the Education Office in Jakarta, which compiled a representative list of Jakarta schools. We randomly sampled households from school rosters and successfully enrolled 308 participants, 285 of whom successfully installed the hardware, connected to Wi-Fi, and operationalized the devices for data collection. Therefore, all our participant households have at least one child at elementary school. Surveying challenges like low participation and high attrition are common in developing country cities (Greenstone, Lee, and Sahai 2021). Our sample strategy was designed to address these challenges and ensure the proper use and return of air quality hardware.

Figure 1a presents the geographic distribution of participating households and demonstrates the wide coverage across the city. Households in our sample are relatively larger and less wealthy than the average Jakarta household but cover a wide range of socioeconomic backgrounds. For more information on how our sample compares to the wider Jakarta population, see Appendix Table A1.

Following enrollment, the survey enumerators visited households to obtain informed consent and administer a baseline survey. This survey captured household demographic information, housing structure characteristics, and beliefs and behaviors related to indoor and outdoor air pollution. Upon consent, air quality hardware was installed in the home for approximately three months, during which it collected continuous indoor air quality data.

**Indoor  $PM_{2.5}$ .** The air quality hardware was composed of a fan equipped with an internal  $PM_{2.5}$  sensor and was installed in each participating household. The sensors were designed to collect  $PM_{2.5}$  data in real time, with readings not visible to respondents. When connected to Wi-Fi, the devices transmitted data to a remote server at five-minute intervals, which were subsequently aggregated to the hourly level for analysis. The hardware was produced by Nafas, a Jakarta-based air quality technology company.

To incentivize households to keep the hardware on, participants received IDR 35,000 (approximately USD 2) every 30 days, contingent on the hardware being connected to Wi-Fi and operational for an average of 14 hours per day. For households without Wi-Fi or unwilling to use their Wi-Fi for the experiment, dedicated Wi-Fi units were installed. To offset electricity costs, participants received an additional IDR 15,000 (approximately USD 1) every 30 days.

**Outdoor  $PM_{2.5}$ .** Our hardware partner, Nafas, maintains over 100 low-cost outdoor sensors across the city. For each household, we calculate a weighted average of air quality readings from the three nearest outdoor sensors, assigning weights inversely proportional to the distance to each sensor. The 63 outdoor sensors used in this study also capture temperature and humidity data, which we use as controls. The outdoor low-cost sensors were installed prior to our study and were not randomly distributed across space, which could introduce non-randomly distributed measurement error. We test for selection in the location of outdoor sensors by regressing a household's distance to the closest outdoor sensor on recorded indoor  $PM_{2.5}$ , recorded outdoor  $PM_{2.5}$  of this sensor, household income, house size, whether the household owns an AC, household head employment status, and household head education level. We do not find evidence of selection bias on observables, as shown in Appendix Table A2.

**Natural ventilation behaviors.** To complement our main survey efforts, we deployed a short WhatsApp survey with participating households on three separate occasions during the study period. The survey asked respondents whether the windows and doors in the room housing the indoor monitor had been open or closed during the past hour.

## 4.2 Infiltration Rate

The average indoor infiltration rate is defined as the increase in indoor  $PM_{2.5}$  concentration per unit increase in local outdoor  $PM_{2.5}$  concentration. To estimate this rate, we used a regression model at the monitor-hour level. For each household  $i$  in hour  $t$ , the infiltration rate ( $\beta$ ) was estimated using the following specification:

$$PM_{it}^{In} = \alpha + \beta PM_{it}^{Out} + \pi T_{it} + \gamma H_{it} + \mu_h + \mu_w + \varepsilon_{it} \quad (1)$$

where  $PM_{it}^{In}$  and  $PM_{it}^{Out}$  denote indoor and outdoor  $PM_{2.5}$  concentrations, respectively;  $T_{it}$  and  $H_{it}$  are controls for contemporaneous outdoor temperature and humidity; hour-of-day controls  $\mu_h$  capture diurnal patterns in pollution and household activities; and week-of-sample controls  $\mu_w$  capture temporal trends and broader atmospheric conditions.

Figure 2a presents the results of this regression model for this main specification and alternative ones:

1. Main specification: includes controls for average variation in  $PM_{2.5}$  over the course of the day (hour-of-day fixed effects,  $\mu_h$ ) and average weekly trends (week-of-sample fixed effects,  $\mu_w$ ).
2. Specification 1 and adds controls for time-invariant differences across households ( $\mu_i$ ).
3. Specification 1 and adds controls for household-specific average variation in  $PM_{2.5}$  at different times of the day (household-hour-of-day fixed effects,  $\mu_{ih}$ ).
4. Specification 1 but restricts the sample to households located within 1 km of a low-cost outdoor sensor to assess the potential impact of measurement error in outdoor  $PM_{2.5}$  concentrations on infiltration estimates.

The estimated infiltration rate ( $\beta$ ) remains highly stable across all specifications. We chose specification 1, which includes hour-of-day and week-of-sample fixed effects, as our main specification to enable us to examine heterogeneity by household-level characteristics, which would not be possible in the presence of household fixed-effects ( $\mu_i$ ).

We further investigate lagged effects of outdoor  $PM_{2.5}$  with the following specification:

$$PM_{it}^{In} = \alpha + \sum_{k=0}^{11} \beta_k PM_{it}^{Out} + \pi T_{it} + \gamma H_{it} + \mu_h + \mu_w + \varepsilon_{it} \quad (2)$$

We present the results including 11 lags (outdoor  $PM_{2.5}$  at each of the previous 11 hours) and ensure that the results are robust to the inclusion of additional lags. From this regression, we derive an estimate of outdoor-indoor infiltration by calculating the cumulative effect of a 1  $\mu g/m^3$  increase in outdoor concentration on indoor concentration:

$$\beta' = \sum_{k=0}^{11} \beta_k \quad (3)$$

Infiltration rates derived from this lagged regression are very similar to our main estimates, given that most of the infiltration happens within the first hour, as shown in Figure A1.

To examine heterogeneity in infiltration rates across household characteristics  $X_i$ , we run the following interacted specification:

$$PM_{it}^{In} = \alpha + \beta_1 PM_{it}^{Out} + \beta_2 X_i + \beta_3 (PM_{it}^{Out} \times X_i) + \pi T_{it} + \gamma H_{it} + \mu_h + \mu_w + \varepsilon_{it} \quad (4)$$

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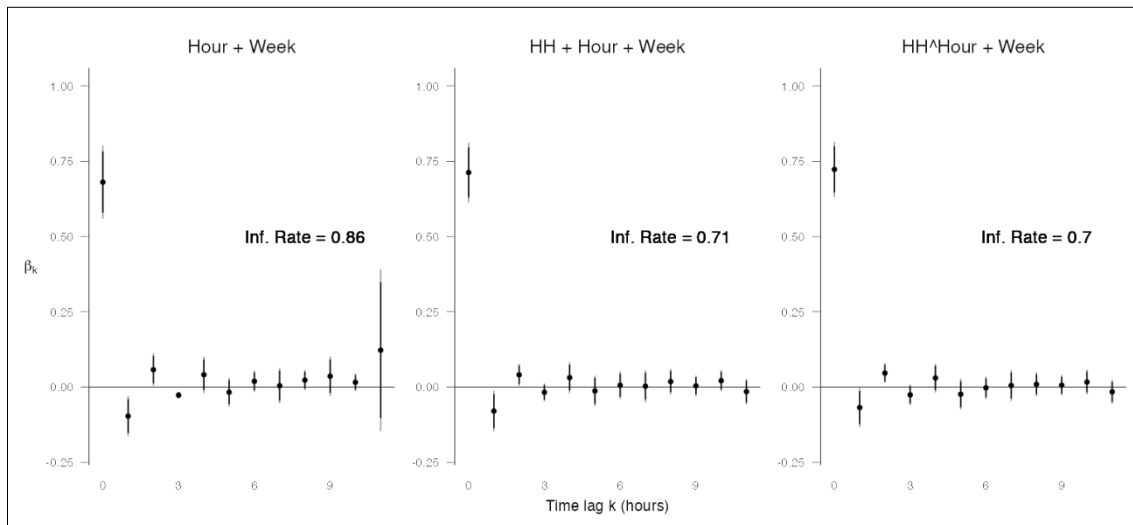
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## APPENDIX

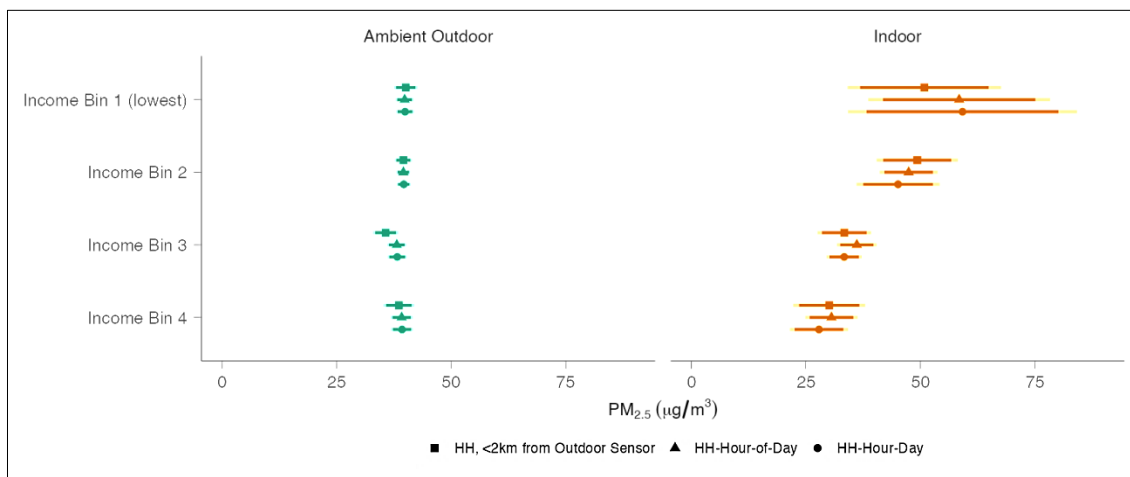
### A.1 Figures

**Figure A1: Infiltration Rate with Lagged Outdoor  $PM_{2.5}$**



Note: (a) Infiltration rate, showing the relationship between changes in outdoor concentration and changes in indoor concentration. This shows the lags in the previous 11 hours. The model controls for hour-of-day and week fixed effects. Points represent mean estimates; darker error bars show 90% confidence intervals and lighter error bars show 95% confidence intervals. Errors are clustered at the household level.

**Figure A2: Robustness: Mean  $PM_{2.5}$  Under Various Aggregation Methods**



Note: (a) Mean  $PM_{2.5}$  concentrations across income quartiles, aggregated using three different methods to show robustness of Figure 4a. *HH, <2km from Outdoor Sensor* calculates a single mean  $PM_{2.5}$  value per household, restricting the sample to households located within 2 km of an outdoor sensor to ensure proximity-based comparability. *HH-Hour-of-Day* aggregates data by computing the mean  $PM_{2.5}$  concentration for each household at each hour of the day. *HH-Hour-Day* uses mean  $PM_{2.5}$  concentrations at the level of each household-hour-date. Mean  $PM_{2.5}$  is then regressed onto the income quartile. Points represent mean estimates; darker error bars show 90% confidence intervals and lighter error bars show 95% confidence intervals. Errors are clustered at the household level.

## A.2 Tables

**Table A1: Summary Statistics of Household Survey**

| Variable                             | Control<br>(mean)  | N   | Population<br>(mean) |
|--------------------------------------|--------------------|-----|----------------------|
| Female                               | 0.91               | 308 |                      |
| Age                                  | 41.01<br>(6.82)    | 308 |                      |
| HH size                              | 5.12<br>(1.9)      | 308 | 3.79<br>(1.31)       |
| Number of children                   | 2.05<br>(1.01)     | 307 |                      |
| HH monthly exp. (USD)                | 248.28<br>(115.96) | 308 | 655.94<br>(707.71)   |
| HH monthly income (USD)              | 308.58<br>(191.39) | 308 |                      |
| HH head attended secondary education | 0.88               | 308 | 0.88                 |
| HH head attended tertiary education  | 0.13               | 308 | 0.3                  |
| Owns AC                              | 0.54<br>(0.5)      | 292 | 0.39                 |
| LPG stove                            | 0.98               | 307 | 0.96                 |
| Number of smokers                    | 0.93<br>(0.84)     | 308 | 0.73<br>(0.71)       |

Notes: Household characteristics and comparisons to the Jakarta population mean. Population means were calculated using data from the National Socioeconomic Survey (SUSENAS) 2023.

**Table A2: Distance to Outdoor Sensor Not Correlated with Household Characteristics**

| Dependent Variable               | Distance to Outdoor Sensor<br>(meters) |
|----------------------------------|----------------------------------------|
| Model                            | (1)                                    |
| <i>Variables</i>                 |                                        |
| Indoor PM <sub>2.5</sub>         | -1.39<br>(2.56)                        |
| Outdoor PM <sub>2.5</sub>        | 3.43<br>(9.29)                         |
| Income (USD)                     | 0.16<br>(0.62)                         |
| Housing size                     | 27.27<br>(55.65)                       |
| AC                               | -167.19<br>(207.76)                    |
| HOH employed                     | 368.26<br>(392.01)                     |
| HOH attended secondary education | -369.00<br>(322.55)                    |
| HOH attended tertiary education  | -211.83<br>(335.16)                    |
| <i>Fit statistics</i>            |                                        |
| Dependent variable mean          | 2,366.6                                |
| Observations                     | 280                                    |

Notes: Regression of households' distance to nearest outdoor sensor on household covariates. IID standard errors in parentheses. Significance codes: \*\*\* 0.01, \*\* 0.05, \* 0.1.