Air Pollution and Time Use: Evidence from India

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How does air pollution impact outdoor activity avoidance? Leveraging changes in local wind direction in an instrumental variable setup, we find a significant reduction in time spent outdoors during polluted days, driven by decreased engagement in employment at the intensive margin. This effect is prominent among self-employers and casual laborers, implying substantial pecuniary costs. We show that visibility in the air is a pivotal mechanism behind the effect, while we do not rule out health and labor productivity-related channels. Reduced time outdoors can also promote a more equitable allocation of unpaid care responsibilities within households via increased male involvement.

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1 Introduction

> *"At the approach of danger there are always two voices ...: one tells to consider the nature of the danger and the means of escaping it; the other says ... it is not in man's power to avert the course of events ..."*
>
> – from *War and Peace* by Leo Tolstoy

Air pollution is dangerous: its effects on health and non-health outcomes are widely documented in both developing and developed country contexts.[1] But we know much less about whether people try to escape or how they respond to the elevated levels of pollution. If these responses take the form of changes in routine behavior and affect everyday interactions, then substantial costs might not be quantified. For instance, more time spent indoors might affect the intrahousehold allocation of tasks among household members. Since these changes take the form of labor market adjustment, the preexisting distortions in these markets may get amplified. If there are also differential responses to the increased air pollution across individuals with different socioeconomic statuses, existing disparities in the negative impact of pollution among these groups might be exacerbated.

The effect of air pollution exposure is, in large part, determined by the choices individuals make. Such choices available to an individual may be driven by their knowledge, beliefs, or preferences (Burke et al., 2022). Without policies limiting exposure, people are compelled to avoid pollution by protecting themselves from its hazardous levels. One way in which these protective behaviors manifest is by undertaking private, often costly, actions to reduce exposure levels. Limiting participation in outdoor activities by reallocating time to indoors is one such action. Equal time endowment across individuals notwithstanding, it is vital to underline that factors like socioeconomic circumstances, information provision, and flexibility drive the ability to undertake reallocation. Though this reallocation does not capture all the aspects of limiting pollution exposure and thus yields lower bounds of the true effect, in developing countries, where many occupations are almost exclusively performed outdoors, reducing time spent outdoors itself entails high pecuniary costs.

In this work, we study how time-use patterns change on exposure to elevated levels of air pollution. We use data from the India Time Use Survey – a large nationally representative dataset that encompasses information about time spent on daily activities and classify an activity as being performed outdoors if and only if no part of the activity can unambiguously be performed within the indoor premises. We then construct the measure of time spent outdoors for each household member aged six years and above and combine these observations

[1] Brewer et al. (2023) summarize existing literature examining the health effects of air pollution exposure. See Aguilar-Gomez et al. (2022) for a review of non-health effects of air pollution.

with the data on air pollution and weather conditions for the district in which the household resides.

To obtain information on air pollution exposure and weather conditions that jointly influence time-use patterns and air pollution concentrations, we use satellite reanalysis data, which provides comprehensive and continuous information at a high spatial and temporal resolution. Our main pollutant of interest is $PM_{2.5}$ – a particulate matter that is 2.5 micrometers or smaller in diameter. Because of their extremely small size, they can penetrate deep into human tissue and cause multiple obstructions to normal functioning. Existing studies, both in the economic and epidemiological literature, have shown robust and consistent negative effects of $PM_{2.5}$ exposure on health and other outcomes (Aguilar-Gomez et al., 2022). Elevated levels of $PM_{2.5}$ can result in smog and other environmental phenomena that are visible to the naked eye, which may prompt residents of the polluted area to reallocate their time across activities, especially those that are performed outside.

To uncover the causal effect of air pollution exposure on time-use patterns, we use an instrumental variables (IV) setup. We rely on an IV design to secure the identification against potential measurement errors in the pollution exposure measure and the possible presence of omitted variables. We instrument for district-level $PM_{2.5}$ concentration measure with an interaction of the district to be in one of the district clusters and the wind direction to be in one of the twelve 30° bins in the spirit of Deryugina et al. (2019). This IV strategy provides plausibly exogenous variation in air pollution concentration driven by idiosyncratic changes in district-level wind directions and requires that a polluting source affect pollution levels similarly for all districts in a given cluster. Hence, the change in pollution levels is driven by sources away from the districts, which obviates requirements for information on local sources of pollution.

The point estimates from our preferred IV specifications (baseline or main estimates) suggest that one standard deviation (SD) increase in daily $PM_{2.5}$ concentration reduces time spent outdoors by 0.04 SD. This is equivalent to a decline of approximately eight minutes, or a 5.1% decline in time spent on activities that are performed outdoors over the sample mean. High first-stage F-statistic suggests that our instruments predict $PM_{2.5}$ concentrations reasonably well. We also find that the relationship between pollution and time spent outdoors is nonlinear: the negative effect is large and statistically significant on days when the existing levels of pollution are higher than normal, while it is insignificant on days with below-normal levels.

Disaggregating the outcome variable, we find that almost all of the decline in time allocated for outdoor activities results from a drop in time spent on employment-related activities. This reduced time is then reallocated to indoor leisure and outdoor unpaid care activities.[2] Further, we show that the reduced time on employment outdoors is an intensive margin effect rather than an extensive margin. In other words, all the adjustment in employment is driven by reducing the extent of such activities and not completely abstaining from them. Indeed, when we examine what time of the day this decline is concentrated, we find that it is situated in the second half of a typical workday.

The baseline effect is mainly driven by respondents who are more likely to be participating in the labor market, i.e., aged between 23 and 60 – an unsurprising result given that the primary role in time reallocation arises from the time saved on employment. Our investigation reveals a monotonic decline in the main effect with education level: reduction in employment outdoors is pronounced for the illiterate, while this effect is absent for those who have completed college.

On one hand, lending credence to the previous finding, we observe that respondents who report being self-employed or casual wage laborers drive the decline in time outdoors. These workers spend significantly more time in employment outdoors and they are also more likely to have flexible work schedules permitting them to adjust labor supply decisions in the short-run. On the other hand, we find no significant effect among regular waged or salaried employees; these workers spend substantially less time in employment outdoors than the self-employed and casual laborers and have lower flexibility in their short-term labor supply decisions that may not provide enough margin to reallocate time away from outdoor employment activities. Consistent with these patterns, we further find that the effect is driven entirely by the high-risk industries (Holub and Thies, 2022), where a typical employee spends most of the time on work outdoors.

The highlighted findings are for short-run reallocation behavior only, as in the medium-to long-run, self-employed and casual laborers may not be able to detach themselves from the labor market. Indeed, only the relatively better-off respondents among the self-employed and casual laborers reduce their time outdoors. Moreover, there might be a dynamic adjustment of labor supply if air pollution levels vary significantly over the short run. For instance, the decline in employment may persist for only a few days if the shift in air pollution level does not subsequently decline. That is precisely what we provide evidence for.

It is important to underline that in this study, we do not aim to disentangle the effects of pollution exposure on labor supply from labor demand but rather focus on the overall

[2] Leisure activities include but are not limited to all types of leisure and entertainment, learning, socializing and communication, community participation and religious practice, culture, mass media and sports practices, and self-care. Unpaid care activities include transportation, unpaid caregiving and domestic services for household and family members, as well as unpaid volunteer, trainee, and other unpaid work. While time spent outdoors on unpaid care activities increases, this rise is primarily due to the additional time spent on activities during commuting from work to home and represents only 12% of the overall decline in outdoor employment time, with the rest of the share accounted for by indoor leisure activities.

employment time impacted. Nonetheless, the findings may suggest that a reduction in labor supply decisions is the primary driver of the decline in employment-related activities.

The magnitude of the estimates implies that an average self-employed or casual laborer would be willing to pay 7.34% of their daily wages to improve the air quality to a level considered safe by the World Health Organization. This translates into approximately $61.22 million in lost daily wages for the overall population.

Notably, the share of male members' time allocated to unpaid care increases on more polluted days, which implies that the reallocation behavior in the household due to the elevated levels of pollution might lead to a more equitable distribution of domestic responsibilities between genders. Nonetheless, two-thirds of the time that females save from employment outdoors is reallocated to unpaid care activities indoors, suggesting a significant influence of gendered norms related to unpaid care in India.

We examine three potential mechanisms for the documented decline in time outdoors. Information about air quality could be a plausible channel through which exposed residents reallocate their time indoors. It is also the case that visually perceptible changes in air quality could be driving the main effect – higher levels of pollution worsen visibility and lead to a more pronounced decline in time outdoors. Finally, adverse health consequences of air pollution exposure may also lead to reduced time outdoors. We find evidence for the visually perceptible changes and health channels but cannot rule out the information channel.

Our findings remain robust through a series of sensitivity analyses. The conclusions are unaltered by changes in the analytical sample, empirical specification, and the presence of co-pollutants, among other empirical checks. We show that non-random selection of households for interviews is not driving the main effect. We also provide evidence that the short-run effect of reduced outdoor time is due to exposure to contemporaneous pollution levels and not to its lag or lead.

With this work, we contribute to multiple strands of literature. First, we contribute to a rich body of literature on the determinants of labor supply (Behrman, 1999). Existing works document the negative effect of air pollution exposure on earnings, employment, and labor force participation (Borgschulte et al., 2022; Hanna and Oliva, 2015; Hoffmann and Rud, 2022). We add to these works by examining the effect of ambient air pollution on time allocated to various labor market activities and quantifying the monetary costs of this adjustment. Our context and findings differ from these studies as the Indian economy is characterized by a high level of informality (La Porta and Shleifer, 2014; Abraham, 2019).[3]

[3]We emphasize significant differences between the labor market structure explored in these studies and ours. Hanna and Oliva (2015) and Hoffmann and Rud (2022) examine the labor market in a highly urbanized city, Mexico City. Borgschulte et al. (2022) on the other hand focuses on the U.S. labor market which is highly formal with significant employee protections. Our study uses nationally representative data from India

Secondly, our work is related to a nascent and active literature on the effect of air pollution exposure on actions people undertake to limit their air pollution exposure (Bäck et al., 2013; Graff Zivin and Neidell, 2009; Ito and Zhang, 2020; Moretti and Neidell, 2011; Neidell, 2009; Saberian et al., 2017; Wang and Zhang, 2023). Building on these existing works that almost always rely on small geographical areas, we provide nationwide estimates of the effects of pollution exposure on time spent outdoors. Our context is India, which has much higher levels of baseline ambient air pollution levels.[4] To the extent that there are non-linearities in the response function of time-use to pollution concentrations, the estimates from existing studies might not be a reliable guide in a more polluted setting. We are also able to leverage our large sample size and detailed individual- and household-level information to study if this effect varies across subpopulations.[5]

Third, we add to the literature that examines the effect of exposure to short-run changes in environmental conditions on time-use patterns (Connolly, 2008; Garg et al., 2020; Graff Zivin and Neidell, 2014). While these works study the effect of changes in weather patterns on time-use, we examine changes in time allocations to various activities due to ambient air quality.

Fourth, we contribute to multiple studies on time use patterns in developing countries by showing that during higher polluted days, male members of the households reallocate their time to unpaid care activities, which in turn allows the female members to spend more time on leisure (Field et al., 2023; Hirway, 2010).[6] Thus, though air pollution exerts large negative effects on various outcomes, it might have an unintended consequence of equalizing intrahousehold allocation of unpaid care across genders.

Finally, we supplement the literature studying myriad effects of air pollution exposure

where the majority of the workers have informal employment with almost nonexistent employee protections and live in rural areas. The potential mechanisms are also different. Unlike the U.S., information on air pollution is only sparsely available in developing countries. Therefore, the residents of these countries do not have enough information about their exposure and may not react effectively to the high levels of pollution. Even if the information on air quality is readily available, prevailing socioeconomic conditions may drive a wedge between developed and developing state residents' responses to its deterioration. Cultural norms and practices intertwined with inertia to modify daily activities might lead to differential effects of air pollution exposure on avoidance behavior between developed and developing countries. By studying a very different labor market structure that has the potential to alter employer and employee adjustments to elevated air pollution concentrations, we provide crucial evidence of how institutional features affect labor market outcomes due to changes in environmental conditions.

[4] Average $PM_{2.5}$ level in India in 2022 was 10.7 times the WHO air quality guideline value - IQAir.

[5] Additional point of departure from these existing works is the identification strategy employed hereby. Specifically, we use an IV setup leveraging changes in air pollution levels generated by changes in local wind direction. These studies rely on variations in smog alert dissemination generated by previously determined arbitrary concentrations of pollutants in a regression discontinuity setup.

[6] Our work is also related to a large literature using time diary data in a developed country context (Aguiar and Hurst, 2007; Aguiar et al., 2021; Biddle and Hamermesh, 1990; Burda et al., 2013; Kalenkoski et al., 2005; Krueger and Mueller, 2012; Stratton, 2012).

in developing countries (Aguilar-Gomez et al., 2022; Chang et al., 2019; Graff Zivin et al., 2023; Greenstone and Jack, 2015; He et al., 2019; Wang et al., 2022).

The rest of this paper proceeds as follows. In Section 2, we describe the employed data and provide summary statistics. In Section 3, we illustrate the empirical strategy and discuss the threats to identification. We then present results in Section 4. Section 5 provides a discussion and concludes.

2 Data

The ideal individual-level data to study the effect of contemporaneous air pollution exposure on time reallocated across various activities will contain complete information on individual and household characteristics, their daily time allocation, and pollution exposure. While such a dataset does not exist, we combine multiple datasets to study the effects of air pollution exposure on the changes in time allocation across various activities. In particular, we obtain time-use information from the India Time-Use Survey (ITUS) and rely on satellite reanalysis data to obtain information on air pollution and weather conditions. In what follows, we describe these datasets in detail and present descriptive statistics. We provide other data sources in the following sections when discussing the results and sensitivity analyses they are employed in.

2.1 India Time-Use Survey (ITUS)

We use a nationally representative survey from India conducted in 2019 to obtain time-use information. ITUS is collected by the Indian National Sample Survey Organization (NSSO) and it surveyed all individuals aged six years and above in 138,799 households. In total, 447,250 individuals were surveyed between January and December 2019. An important aspect of the sampling design is that it allocates the sample equally across sub-rounds (quarters) spread over the year to ensure representation of different seasons in the data collected (NSSO, 2020). We return to this point in greater detail in Section 3.

ITUS collected information on individuals' time-use for 24 hours starting from 4 A.M. on the day before the interview to 4 A.M. on the interview date. These 24 hours are further split into 48 time slots of 30 minutes duration each. Each respondent is asked about the activities they performed in each time slot. Further, the respondents are instructed to report "major" activity in case multiple activities are performed in a given time slot. The survey treats an activity as "major" if the informant considers it the most important activity performed during a given time slot. The survey suggests two ways to calculate the time spent on an activity in a given time slot: the first assigns the entire duration of the time slot to the reported major activity, and the second assigns the duration of the time slot equally among all the reported activities in that time slot. We present results using both approaches by labeling them as “only major” and “both major and minor” activities, respectively. To classify the activities into various categories, we rely on three-digit codes from the 2016 International Classification of Activities for Time Use Statistics (ICATUS), as used by ITUS.

The survey also collects information on the demographics of the household members. For our analysis, we use information on age, gender, highest education level, and usual principal activity status (whether the household member is employed, unemployed, or not in the labor force) of the household members. Additionally, we use household-level information on the number of members in the household, religion, usual monthly consumption expenditure, social group, and primary source of energy for cooking. Usual monthly consumption expenditure is the sum of all expenditures on goods and services consumed by the household for domestic purposes in a given month.

Our main outcome of interest is the amount of time that the respondent spends outdoors. Following the classification of activities as being performed indoors or outdoors in Graff Zivin and Neidell (2014), we classify an activity as being performed outdoors if and only if the description of that activity clearly points to it being performed outdoors and certainly cannot be performed within any indoor premises. We present three-digit codes and descriptions of activities classified as outdoors in Table C1.[7]

2.2 Satellite Reanalysis Data

To obtain information on pollution measures, namely, the main pollutant of interest – $PM_{2.5}$ and other pollutants (ozone, nitrogen dioxide, sulfur dioxide, nitrogen oxide, and carbon monoxide), we use CAMS-EAC4 satellite reanalysis data (Inness et al., 2019). These data are produced by using atmospheric and chemical modeling that combines information from satellite-derived aerosol optical depths, available at a high spatial and temporal resolution. In particular, we use data that have a horizontal resolution of approximately 80 km ($0.75° \times 0.75°$) and a three-hour temporal resolution. These data have been used previously in the Indian context and provide a consistent spatial and temporal measure of air pollution concentrations in a setting where ground-based monitors are not widespread (Craigie et al.,

[7]In Table C2, we show that our main results are robust to using the survey definition of whether the activity is performed “within premises of the dwelling unit of the selected household”. Classifying activities as being performed outdoors, where the description suggests that not all but most tasks are done outdoors (“Relaxed Classification”), also does not substantially alter our conclusions. From these alternate classifications, we obtain qualitatively similar results as with our main classification.

2023). Moreover, in Figure C1, we show that the CAMS-EAC4 satellite reanalysis data that we use for our main specifications correlates well with ground-based monitor data. To establish the robustness of our results to particular satellite reanalysis data used for air pollution measures, we also show results using air pollution concentrations derived from MERRA-2 (Gelaro et al., 2017).

It is worth emphasizing that satellite reanalysis data have been shown to underestimate the actual pollutant concentrations at higher levels in contrast to monitor data (Fowlie et al., 2019). Therefore, to the extent that we find a negative effect of air pollution exposure on time spent outdoors, our estimated effect can be interpreted as a lower bound of the true effect of air pollution exposure on time spent outdoors as long as the relationship between air pollution and time outdoors is monotonic.

To control for weather conditions that can jointly affect time-use and air pollution levels, we obtain information on surface temperature, precipitation, and wind speed from ERA5-Land climate reanalysis data (Connolly, 2008; Garg et al., 2020; Graff Zivin and Neidell, 2014; Muñoz Sabater et al., 2021). These data are available at a high spatial (we employ a horizontal resolution of approximately 10 km ($0.1° \times 0.1°$)) and temporal (hourly) resolution. These data are derived from satellite reanalysis where the forecast models are tuned with the available observational data on climatic conditions (Parker, 2016).

To combine survey and satellite reanalysis data, we perform a matching exercise using districts as the spatial units. Section Appendix A provides details of the analytical sample construction process.

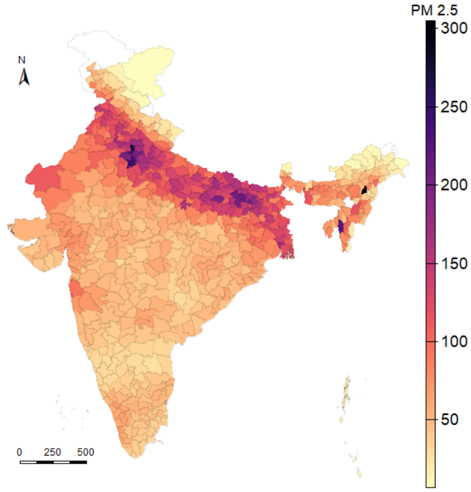
2.3 Descriptive Statistics

To account for the complex survey design, we weight our observations using weights provided by the National Sample Survey Organization (NSSO). Summary statistics show that the analytical sample is evenly distributed between males and females, with three-fourths of the respondents being married at the time of the survey and more than three-fourths of the respondents being literate.[8] Almost a quarter of all respondents are self-employed, and almost 30% of respondents supply labor for wages either regularly or casually. The rest of the respondents are either unemployed or not in the labor force. Later, we examine if the effect of air pollution exposure on time spent outdoors differs across these and other subpopulations. More details about the summary statistics are presented in Table C3.

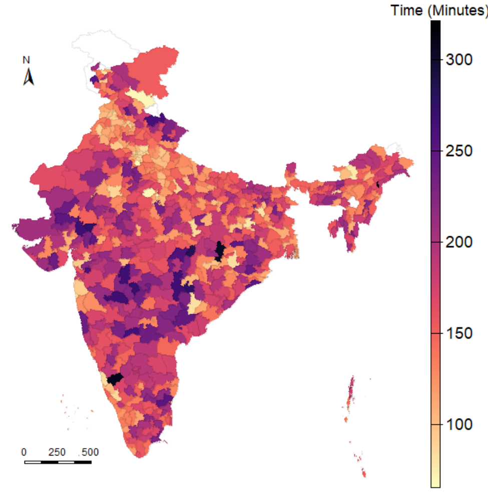
Figure C2 shows the mean $PM_{2.5}$ concentration and associated 95% confidence intervals for each day of the year (in Table C4, we present descriptive statistics for the pollution

[8]ITUS considers a respondent to be literate if they can read and write a simple message with understanding in at least one language.

Figure 1: Spatial Variation in $PM_{2.5}$ Concentration and Time Outdoors



(a) Air Pollution Concentration



(b) Time Spent Outdoors

Note: $PM_{2.5}$ concentration in $\mu g/m^3$, illustrated on the left panel, is averaged over all the days on which at least one interview is conducted in the district using the arithmetic mean. Time spent outdoors in minutes, on the right panel, is averaged for all the respondents in a given district across all days in the sample using the arithmetic mean. The right panel uses time division, where the time on all activities in the time interval is distributed equally among the activities in that time interval. Figure C3 also presents "only major" time division in the third panel. The district polygons come from India's 2011 Census.

and weather conditions). We note that there is substantial temporal variation in the $PM_{2.5}$ concentrations across the year. Summer and monsoon months have lower levels of air pollution, whereas the contrary is true for winter months. In our empirical strategy, we explicitly account for this seasonality in air pollution concentrations and in a robustness analysis allow seasonality to vary by regions. Figure 1 presents the spatial variation in air pollution measures as well as the time spent outdoors. We highlight that the Indo-Gangetic plains have high levels of air pollution. In the second subfigure of Figure 1, we see that time spent on activities performed outdoors is also lower in this region relative to other less polluted regions of the country.

Motivated by this observation, to examine if there is a decline in the time spent on outdoor activities when the outside pollution level is high, we compare time spent indoors and outdoors depending on whether the air pollution concentration is below or above 100 $\mu g/m^3$ in Table 1.

We observe that time spent outdoors is, on average, 21 minutes lower on highly polluted days. In what follows, we examine if this decline can be given a causal interpretation. In the next section, we outline the empirical strategy that we adopt to this end.

Table 1: Time Spent Indoors vs Outdoors

	$PM2.5 \leq 100\mu g/m^3$		$PM2.5 > 100\mu g/m^3$		Difference
	Indoors	Outdoors	Indoors	Outdoors	Outdoors
Panel A: Both Major and Minor Activity					
Time (minutes)	1276.831	163.169	1297.933	142.067	-21.102***
	(185.681)	(185.681)	(178.833)	(178.833)	(0.757)
Panel B: Only Major Activity					
Time (minutes)	1272.126	167.874	1295.316	144.684	-23.190***
	(193.004)	(193.004)	(184.821)	(184.821)	(0.786)

Notes: Standard deviations and standard errors are in parentheses. The final column is the difference in time spent on outdoor activities between high and low polluted days. Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60. Respondents who do not report their gender as either male or female are dropped. Activities classified as outdoor are discussed in the main text. The number of observations in each column is 314,125. The sample contains data from the India Time Use Survey (ITUS) 2019.

3 Empirical Strategy

We start discussing our empirical strategy by detailing a fixed-effects specification, which we estimate using Ordinary Least Squares (OLS), and why this specification might produce biased estimates. To uncover consistent estimates of the effect of air pollution exposure on time allocated for various activities, we use an instrumental variable (IV) setup and discuss identification along with the estimation of this specification.

We estimate the following fixed-effects specification using OLS:

$$y_i = \alpha_{i(d)} + \alpha_{i(t)} + \beta PM2.5_{i(d,t)} + \mathbf{W}_{i(d,t)}\pi + \epsilon_i \tag{1}$$

This specification includes fixed-effects for the district of respondents' residence and time. Time fixed-effects, $\alpha_{i(t)}$, enter the specification through fixed-effects for calendar date. District fixed-effects, $\alpha_{i(d)}$, control for time-invariant district-level unobservable characteristics, such as the topography of the district. Time fixed-effects control for unobservable factors common to all districts on a given calendar date. These include factors like big national sports events that affect time-use. Failure to account for both these sets of fixed-effects would confound our estimates as we would misattribute the effect of such factors on time-use to air pollution.

We control for weather conditions that might be correlated with air pollution concentration and time-use in vector $\mathbf{W}_{i(d,t)}$. This vector of weather conditions includes precipitation, temperature, and wind speed. In Equation (1), y_i is the outcome of interest. In almost all specifications, this is the amount of time spent on various activities in minutes.[9] ϵ_i is an idiosyncratic error term that we cluster at the district of residence level to allow for correlation across households within a district (Abadie et al., 2022). β is our parameter of interest, which is the marginal effect of a unit change in $PM_{2.5}$ concentration on the outcome variable.

The variation used in the regression comes from comparison across individuals who live in the same district but are exposed to different levels of air pollution because they are surveyed on different dates. The sampling strategy adopted by NSSO is such that the survey dates are spread over the entire year (NSSO, 2020). To examine this further, we check the distribution of survey dates across quarters for every district. Figure C4 shows that barring a few exceptions, survey interviews were held in all the quarters for most of the districts.[10] This indicates that different regions of the country were surveyed throughout the year, alleviating any concern of region-specific seasonality driving the estimates. In robustness analysis, we also show that the number of interviews conducted in a day is not affected by the pollution levels and our results hold even after controlling for state-specific month fixed effects.

While the specification in Equation (1) leverages within district and over time changes in air pollution levels after purging out the effects of secular shocks and weather conditions, the estimated effect may still be biased.[11] To assuage concerns related to the endogeneity of air pollution exposure, we turn to an IV setup relying on existing work that leverages changes in local wind directions to instrument for district-level air pollution levels (Deryugina et al., 2019). We estimate the IV setup using the following first-stage specification.

$$PM2.5_{i(d,t)} = \alpha_{i(d)} + \alpha_{i(t)} + \sum_{k=1}^{40}\sum_{b=2}^{12} \theta_{k,b}\mathbb{1}\left(i\left(d\right) \in k\right) \times \mathbb{1}\left(\omega_{i(d,t)} = b\right) + \mathbf{W}_{i(d,t)}\pi + \mu_i \tag{2}$$

In Equation (2), all parameters are the same as in Equation (1) except for $\theta_{k,b}$, which is the parameter on the interaction of an indicator variable for the district of respondents' residence

[9] When this is not the case, we detail what the outcome variable is when we discuss specific results.

[10] Approximately 56% of the districts have interviews in all four quarters of the calendar year, while 81.36% have interviews in at least three quarters. Even if we restrict the analytical sample to only those districts covered in all the four quarters, the estimates are extremely similar to the baseline point estimates, in terms of magnitude and statistical significance. For instance, considering "both major and minor activity", the point estimate on $PM2.5$ is -0.090 and significant at the 5% level.

[11] This could happen due to either the measurement error in the pollution exposure or unaccountable omitted time-varying variable bias - OVB. Conceivably, air pollution varies within districts, thereby leading to measurement error in the pollution concentration measure. As long as the measurement error in air pollution concentrations is not systematically related to time-use patterns, our estimated effect of air pollution exposure on time allocation will be an underestimate of the true effect. OVB might also lead to biased estimates, where the direction of the bias would be ambiguous.

d to be in cluster k, $\mathbb{1}(i(d) \in k)$, and wind direction for the district of residence d on the date of survey t to be in bin b, $\mathbb{1}\left(\omega_{i(d,t)} = b\right)$.

Using the k-nearest neighbors algorithm, we cluster districts into 40 clusters. This non-parametric supervised learning classifier uses only the longitude and latitude information of the district centroid to classify districts into multiple clusters. Ideally, we would like to have each district as its own cluster. However, due to the sample size, this specification is not computationally feasible. We later establish the robustness of our results by using different numbers of clusters to classify districts (see Table C5). In Figure C5, we show the cluster to which each district is assigned. We use 12 wind direction bins, each of 30° interval. The omitted wind direction bin is $[0°, 30°]$. In all our IV specifications, we present first-stage F-statistics to establish the strength of our excluded instruments.

Our IV design captures variations in the district-level air pollution levels driven by changes in local wind direction. While we allow wind directions to vary by district, we force a given wind direction to have the same influence on the air pollution levels for all districts in a given cluster of districts. This essentially means that the change in district-level air pollution is driven by sources further away from where the pollution is blown to the downwind districts. We further discuss the details of our identification strategy, potential threats, and the ways we address them in Appendix B.

In Appendix Figure C6, we show how the air pollution levels and time spent on outdoor activities change within a given day. We note that air pollution levels exhibit a U-shape. In contrast, the time spent on activities outdoors exhibits an opposite - inverted U-shape.[12] The negative relationship in this figure is stark, and our empirical strategy aims to investigate whether this relationship holds up when we leverage plausibly exogenous variation in pollution exposure.

Since we use two-stage least squares (2SLS) estimation for our IV setup, the second-stage is given by the following specification:

$$y_i = \alpha_{i(d)} + \alpha_{i(t)} + \beta \widehat{PM2.5}_{i(d,t)} + \mathbf{W}_{i(d,t)}\pi + \nu_i \tag{3}$$

In Equation (3), all parameters are the same as in Equation (1) except for $PM_{2.5}$ which is now predicted in the first-stage and denoted by $\widehat{PM2.5}$. We next discuss results from

[12] It is not surprising that the air pollution levels do not suddenly increase in the morning rush hour when the vehicular emissions are probably at their peak. Existing work has demonstrated a consistent diurnal pattern in air pollution levels (Chen et al., 2020; Sreekanth et al., 2018). Starting from early afternoon, around 3 PM, the pollution concentration starts rising, with some cities experiencing peak pollution at night. The pattern in Figure C6 also documents this pattern. As the vehicular emissions due to the morning traffic rush persist only for a few hours, the attenuation of the decline in the air pollution levels in our coarse three-hour $PM2.5$ measure suggests that our air pollution measure is able to capture the intraday variation in air pollution levels, albeit with some noise.

estimating Equation (1) - (3) for various outcome variables.[13]

4 Results

In this section, we present the main results and establish the robustness of our conclusions through a series of empirical checks. We examine if the main effects vary across different subpopulations. In particular, we study whether time allocated to distinct activity types differs when the air pollution levels change. Our heterogeneity analysis also provides evidence for significant differences in the time-use response function of air pollution by demographic characteristics of the respondents. After establishing that respondents reduce time on outdoor activities, we document an increase in the male share of time on unpaid care activities suggesting more gender-equal intrahousehold allocation of unpaid care activities. Upon examining what time of day the reallocation across activities happens, we highlight the role of working hours. We conclude the section by studying potential mechanisms that might be leading to changes in time-use patterns due to elevated air pollution levels that we uncover.

4.1 Main Results

Table 2 presents the results from our main specifications – both OLS estimation of Equation (1) and 2SLS estimation of Equations (2) - (3). In the top panel, multiple activities in a given time slot are assigned equal time. In the bottom panel, only a major activity is assigned the entire time duration for a given time slot (see Section 2.1 for more details). As we move across the table, we employ controls and fixed-effects, eventually leveraging variation in air pollution concentrations within a district after purging out the secular changes in air pollution concentrations and time use patterns through calendar date fixed-effects to identify the causal effect of air pollution exposure on time spent outdoors.

In our preferred specifications in the last column, the IV point estimate suggests that one standard deviation (SD) increase in $PM_{2.5}$ concentration reduces time spent on outdoor activities by 0.04 SD. This decline in time outdoors is equivalent to approximately eight fewer minutes outdoors. This corresponds to a 5.1% decline in time spent outdoors over the sample mean (2.6 hours). We also note that in the first-stage, our instruments predict $PM_{2.5}$ concentration levels reasonably well, as evidenced by a high Kleibergen-Paap F-statistic.[14] Furthermore, estimates in both the top and bottom panels are similar, albeit the bottom

[13]Wherever necessary, we also detail other specifications that we estimate that are not a variant of these equations.

[14]The Hansen J-Statistic p-value for the overidentification test is 0.50, indicating that our instruments pass the overidentification test.

Table 2: Effect of Air Pollution on Time Spent Outdoors – Main Effect

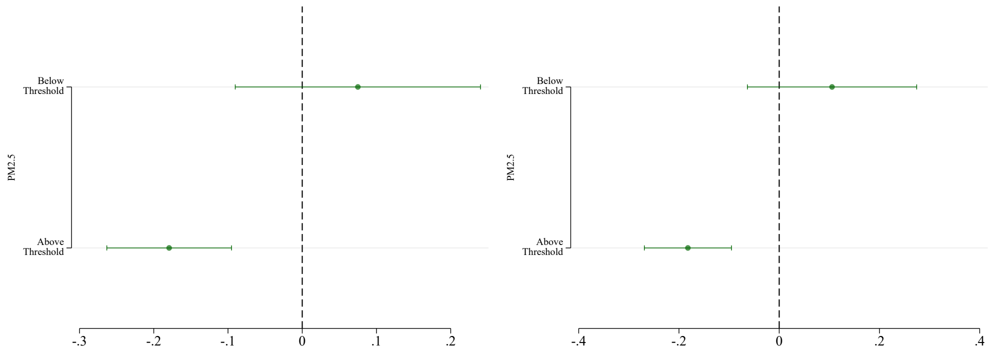
	OLS (1)	OLS (2)	OLS (3)	IV (4)
Panel A: Both Major and Minor Activity				
$PM2.5\,(\mu g/m^3)$	-0.023*	-0.035**	-0.032**	-0.109***
	(0.013)	(0.014)	(0.015)	(0.036)
Weather Controls		✓	✓	✓
District FE	✓	✓	✓	✓
Day-of-Week FE	✓	✓		
Month FE	✓	✓		
Calendar Date FE			✓	✓
Dep. Var. Mean	157.875	157.875	157.875	157.875
Dep. Var. SD	184.214	184.214	184.214	184.214
Indep. Var. SD	73.661	73.661	73.661	73.661
KP F-Statistic				133.151
N	314,125	314,125	314,125	314,125
Panel B: Only Major Activity				
$PM2.5\,(\mu g/m^3)$	-0.022*	-0.033**	-0.031**	-0.104***
	(0.013)	(0.014)	(0.015)	(0.036)
Weather Controls		✓	✓	✓
District FE	✓	✓	✓	✓
Day-of-Week FE	✓	✓		
Month FE	✓	✓		
Calendar Date FE			✓	✓
Dep. Var. Mean	162.057	162.057	162.057	162.057
Dep. Var. SD	191.248	191.248	191.248	191.248
Indep. Var. SD	73.661	73.661	73.661	73.661
KP F-Statistic				133.151
N	314,125	314,125	314,125	314,125

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The dependent variable in all columns is the amount of time spent on outdoor activities in minutes. Activities classified as outdoor are discussed in the main text. Specifications in column (2) to column (4) add weather controls. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables in the specifications of column (4) are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

panel has slightly attenuated effects. We benchmark our effect sizes relative to the existing literature in Section 5.

We postulate that the effect of pollution on time spent outdoors is nonlinear; specifically, a marginal increase in $PM_{2.5}$ concentration may have different effects based on whether the existing level of pollution on a day is low or high. To investigate this hypothesis, we construct a binary indicator identifying each day of survey as either below or above the normal level of pollution. We define the normal threshold for each district as the median

Figure 2: Non-linear Effect of $PM2.5$ Concentration on Time Outdoors



(a) Both Major and Minor Activity (b) Only Major Activity

Note: Point estimates on the $PM_{2.5}$ concentration variable are plotted on the horizontal axis. Heteroskedasticity robust standard errors clustered by the district are used to construct the confidence intervals. Horizontal lines show 95% confidence intervals. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The dependent variable for all specifications is the amount of time spent on outdoor activities. Activities classified as outdoor are discussed in the main text. The division of time across multiple activities during each 30-minute time interval is denoted in the subfigure caption. In each subfigure, the survey date is classified as being above or below the median of the district's $PM2.5$ concentration in 2018. Each specification includes weather controls, district, and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. The indicator for the $PM2.5$ level to be above the threshold, $PM2.5$ concentration, and an interaction of the indicator variable and $PM2.5$ concentration are instrumented in the estimating specification. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019. The vertical line in each panel corresponds to zero.

level of $PM_{2.5}$ of that district in 2018; using data on pollution from the previous year for this purpose ensures that the threshold itself is not affected by contemporaneous variation in pollution. We interact the main $PM_{2.5}$ variable with this binary indicator and estimate the 2SLS specification considering three endogenous variables (the indicator, $PM_{2.5}$, and their interaction) and the same set of instruments. The findings presented in Figure 2 support our hypothesis – a marginal increase in $PM_{2.5}$ has no significant effect on time spent outdoors on days when the existing level of pollution is below the normal threshold but the effect is significant, negative, and larger in magnitude on days with above normal levels of pollution.

4.2 Robustness Checks

We conduct multiple sensitivity tests to establish the robustness of our findings. Table C6 illustrates the robustness of our results using alternate samples. In the first column of the table, we repeat our baseline estimate from the preferred specifications. In the following column, we use information on the type of day for which the respondent reports the time allocation. ITUS classifies a day for which the time diary is reported as either "normal" or "other".[15] Our point estimates suggest that the main effect is not sensitive to restricting the sample to "normal" days. The point estimate in column (2) is very close to the point estimate in the first column. In column (3), we drop observations for which the respondents report spending time outdoors, which is above the 95th percentile of the sample distribution.[16] While our results are attenuated relative to the baseline when we drop these extreme observations, we continue to find a statistically significant decline in outdoor activities on more polluted days.

In column (4) of Table C6, we show that our main effect is robust to the inclusion of all members of the households who are above the age of six years, irrespective of their reported gender. Using this extended sample of respondents we find an attenuated effect of air pollution exposure on time spent on activities performed outdoors, although this effect continues to be statistically significant. Next, we use an alternate data source to construct measures of $PM_{2.5}$ concentration – MERRA-2 satellite reanalysis data. With the alternate data, we confirm the negative effect of air pollution exposure on outdoor time, albeit with statistically insignificant estimates.[17]

In the next two columns of Table C6, we show that our main effect is not sensitive to adding district-level linear time trends or when we include the gender of the respondent in our main specification. The preceding discussion is not altered by whether we consider both "major" and "minor" activities to allocate time to activities within an interval or only the "major" activity. In the next column, we control for nonlinear effects of weather conditions by including an indicator for the quintile of the weather condition variables. Controlling for weather conditions non-linearly leads to remarkably similar estimates as those reported in the first column.

There can be variation in seasonality across different regions of the country, especially with respect to crop cycles and agricultural practices that can affect pollution and labor supply at the same time. Therefore, we control for state-specific month fixed effects in column (9); our results remain robust in this specification. Overall, results in Table C6 help

[15] A day is designated as "normal" if the respondent performed routine activities. If, for any reason, the respondent cannot perform their routine activities, the corresponding day is designated as "other". Weekly off-days, holidays, and days of leave are also designated as "other" days.

[16] By restricting the estimating sample in this way, we aim to establish the robustness of our results by dropping respondents who report extreme values of time spent outdoors.

[17] The point estimate when using MERRA-2 data is broadly comparable with (albeit slightly larger than) the baseline point estimate and it is marginally insignificant at conventional levels of significance. The measure provided by this alternative data source is less preferred due to the following reason. MERRA-2 does not produce particulate matter concentration measures directly. Instead, other atmospheric particle concentrations are used with a static formula to produce particular matter concentration. Lack of variability across space and time in the formula used to derive particulate matter concentrations might induce higher inaccuracies (Jin et al., 2022).

us conclude that our main effect is not sensitive to various changes we make to the estimating sample or alternative specifications.

Our empirical strategy leverages variation within districts in the interviews conducted on days with different levels of pollution. If the number of interviews differs across less and more polluted days, the estimates might be biased by the non-random selection of households for interviews. To assuage these concerns, we examine if the number of interviews conducted at the district-level is affected by the air pollution concentration in the district.[18] We find no effect of air pollution levels on the number of interviews conducted in the district, which reassures us that our point estimates are not conflated due to the non-random selection of households for interviews on less and more polluted days.

Next, we address the concern that the point estimates might be conflated by the effect of other pollutants on time allocation.[19] We first replace the $PM_{2.5}$ concentration levels with ozone, NO_2, and SO_2 concentrations in Equations (2) - (3). We also present results from a specification where we augment Equations (2) - (3) with concentration levels of these other pollutants. We present results from these specifications in Table C8. We conclude that our main effects are not confounded by the presence of other pollutants that might be correlated with $PM_{2.5}$ (column (5) of Table C8).[20] Further in Table C9, we find that finer particulate matter leads to a larger decline in time outdoors for each unit increase in its concentration level.

We examine if our main effects are altered by the number of clusters to which the districts can be assigned in Table C5. Recall that in our main specification, we restrict the number of clusters to 40. Although our point estimates get attenuated when we use a smaller number of clusters, we continue to find negative point estimates, which suggests that our main effect of air pollution on time use is not driven by the number of clusters. We also show that our main findings are robust to using alternate instrumental variables for air pollution concentrations.[21]

[18]For each day during which interviews are conducted in our sample, we construct a measure of the number of interviews conducted at the district-level for that day. We then regress this measure on the $PM_{2.5}$ concentration, controlling for weather conditions, district, and calendar date fixed-effects. We instrument air pollution concentrations using the same instruments that we use in estimating Equation (2). We present results from estimating these specifications in Table C7. Note that since the number of interviews measure is at the district-day-level, we do not present estimates separately by time division across "major" and "minor" activities.

[19]The data for these pollutants are derived from CAMS-EAC4, the same data source that we use to construct our measures of $PM_{2.5}$ concentrations. We note that when the estimating specification includes more than one pollutant, we use the same set of instrumental variables as in Equation 2.

[20]Null effect for other pollutants except the particulate matter is not surprising given the weak correlation that has been observed of such pollutants with particulate matter in India (Kumar and Pande, 2023; Manimaran and Narayana, 2018).

[21]We draw on the IV setup of Graff Zivin et al. (2023). This setup is inspired by the IV design in Deryugina et al. (2019) but uses far fewer instruments. The air pollution measure for each geographic unit in a given

While the main regressor, pollution concentration, is constructed at the district-level (at which we cluster standard errors in our baseline specification), our outcome variables are measured at the individual level. In such scenarios, it might be the case that the standard errors are too conservative (Abadie et al., 2022). To assuage this concern, we perform randomization inference. We randomly permute the pollution and weather condition measures observed within the sample and then estimate the baseline specifications with these measures. We repeat this process 500 times. The distribution of the point estimates on the pollution concentration measure variable from this bootstrapping approach is depicted in Figure C7. We see that none of the bootstrapped point estimates are lower than our baseline estimates; hence, we conclude that our main effect is robust to the measure of uncertainty used for inference.

We conclude the discussion on the robustness checks by testing if controlling for air pollution lag and lead affects our baseline effects. Earlier work examining the impact of weather conditions on time-use patterns suggests intertemporal allocation as a behavioral response to short-run changes in weather conditions (Connolly, 2008; Graff Zivin and Neidell, 2009; Graff Zivin and Neidell, 2014). Building on this existing work, we examine if elevated pollution levels result in intertemporal reallocation of activities that are performed outdoors. We augment specifications in Equation (1) - (3) by including lag and lead of $PM_{2.5}$ concentration and instrument these air pollution measures with the same set of instruments as that in the main specification.[22] Results in Table C10 show that neither the lag nor the lead of air pollution concentration statistically significantly affects contemporaneous time spent outdoors.[23]

wind direction bin is demeaned using the average air pollution measure over the entire sample for this unit. This approach reduces the dimension of the instrumental variables vector while leveraging the local wind direction driven changes in air pollution levels.

[22]We are unable to use the instruments corresponding to the lag or lead of air pollution due to high correlation between the local wind direction across consecutive days. In column (3) of Table C10, we use instruments drawn from the IV framework in Graff Zivin et al. (2023). In this column, instruments corresponding to lag and lead measures of air pollution are used. The conclusion does not change across column (2) and column (3) of this table even though the two columns use very different sets of instruments.

[23]Due to significant collinearity of pollution measures across consecutive days, the contemporaneous air pollution measure is no longer statistically significant but continues to be negatively associated with time outdoors. In general, the absence of an effect on the lag of pollution measures is surprising as some activities are spread over multiple days to accomplish certain tasks. Later, we examine if this effect is driven by the flexibility afforded by certain employment activities. To the extent that the reduction in time spent outdoors is due to activities related to employment, we expect that more flexible work arrangements dampen the intertemporal reallocation of time spent outdoors.

4.3 Heterogeneous Effects

4.3.1 Heterogeneity by Broad Activity Classification

To examine how the time spent on a broad group of activities changes due to exposure to higher levels of air pollution, we use information on the reported three-digit activity code and the description of these activities from 2016 ICATUS. We group activities based on their first digit. We create four mutually exclusive and collectively exhaustive groups consisting of activities that are related to: (a) employment, (b) producing goods for own final use, (c) unpaid services, and (d) leisure.[24]

We present results from examining the differential effect of air pollution exposure on time allocation within these four groups in Table 3. We find that almost all of the decrease in time spent outdoors results from employment-related activities, and this reduced time is almost entirely reallocated to activities related to leisure indoors or outdoor activities related to unpaid care.[25] It is worth emphasizing that while time spent outdoors on unpaid care activities does go up, this increase constitutes only approximately 12% of the time reallocated from time outdoors and likely comes from transportation from an early-ended workday to home and running errands such as grocery shopping and picking up children along the way. Furthermore, despite being marginally statistically insignificant, the reallocation of time from outdoor activities to unpaid care indoors is substantial at almost 33%. Indeed, when we use the entire sample of respondents in Table C11, the unpaid care indoor coefficient is highly statistically significant.

The reduced time on employment-related activities outdoors is driven by a reduction in time spent on such activities at the intensive margin only instead of completely abstaining from these activities. Table C12 provides evidence in favor of this conclusion. This result is further bolstered by findings in Section 4.3.4 that time outdoors declines during the second half of the working day (1 PM to 7 PM).

These results together suggest that reduced time outdoors might be emanating from the early conclusion of the workday. Stratifying the sample by whether the respondent is an employer or non-employer, Table C13 shows that estimates for reduced time outdoors are slightly more pronounced for non-employer respondents but do not differ statistically from

[24]Employment-related activities have one as the first digit in the three-digit activity code. Activities related to producing goods for own final use have two as the first digit in the three-digit activity code. Activities for group based on unpaid care activities are those for which the first digit of the three-digit activity code is three, four, or five. Activities for the final group are those for which the first digit of the three-digit activity code is six, seven, eight, or nine.

[25]Respondents' age does not drive the effect observed for outdoor activities related to employment. In Table C11, we show that our result on employment-related outdoor activities is unaltered by using all the respondents above the age of six.

Table 3: Heterogeneity by Major Activity Classification – Full Table

	Indoor				Outdoor			
	Employment	Production For Own Use	Unpaid Care	Leisure	Employment	Production For Own Use	Unpaid Care	Leisure
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Both Major and Minor Activity								
$PM2.5\,(\mu g/m^3)$	-0.007	0.003	0.038	0.076**	-0.106***	-0.012	0.017***	-0.009
	(0.032)	(0.004)	(0.024)	(0.037)	(0.032)	(0.019)	(0.006)	(0.006)
Dep. Var. Mean	114.984	1.624	181.731	983.786	99.663	28.273	16.586	13.353
KP F-Statistic	133.152	133.152	133.152	133.152	133.152	133.152	133.152	133.152
N	314,125	314,125	314,125	314,125	314,125	314,125	314,125	314,125
Panel B: Only Major Activity								
$PM2.5\,(\mu g/m^3)$	0.002	0.003	0.040*	0.058	-0.100***	-0.010	0.016**	-0.010
	(0.033)	(0.004)	(0.024)	(0.036)	(0.033)	(0.019)	(0.006)	(0.006)
Dep. Var. Mean	121.250	1.765	191.967	962.962	103.226	29.386	15.559	13.886
KP F-Statistic	133.152	133.152	133.152	133.152	133.152	133.152	133.152	133.152
N	314,125	314,125	314,125	314,125	314,125	314,125	314,125	314,125

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The dependent variable in all columns is the amount of time spent on outdoor activities in minutes. Activities classified as outdoor are discussed in the main text. Nine activity divisions based on the first digit of the three-digit activity code from ICATUS 2016 are further classified into four major divisions. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

the employer respondents (p-value: 0.838). While data constraints restrict our analysis in this dimension to comparing employer and non-employer groups only, the findings suggest that adjustment in employment time outdoors is not exclusively driven by a reduction in employer labor demand.[26]

Particularly, the activities related to agriculture are chiefly responsible for reduced time outdoors on employment activities (Table C14). To highlight the activities related to unpaid care that are performed outdoors, to which reduced time outdoors from employment-related activities is partially reallocated, we examine two- and three-digit activity codes related to such activities (Table C15). Results show increased time outdoors related to unpaid domestic services involving travel related to goods and household members. When uncovering the activities related to leisure that lead to increased time spent indoors arising due to reallocation from time saved forgoing outdoor activities (Table C16), findings suggest that the increased time on indoor leisure activities emanates from increased time spent socializing and communicating and greater use of mass media.

[26]Statistically, the possibility that employers decide to shorten the length of the workday on a highly polluted day is not ruled out, in which case, the reduced time on employment could be attributable to the employers.

Overall, these results suggest that on exposure to elevated levels of air pollution, people respond by reducing time spent outdoors on activities related to employment. Saved time is reallocated to activities related to leisure that are performed indoors and by a small degree on activities related to unpaid care activities related to unpaid care that are performed outdoors.

4.3.2 Heterogeneity by Individual & Household Characteristics

Does the effect of air pollution exposure on time spent outdoors differ by the respondent's age?[27] Estimations show that our main effect is driven by respondents who are more likely to be participating in the labor market (Figure 3).[28] We do not find a statistically significant effect for respondents who are either most likely to be enrolled in educational institutions or are over 60 years old and not actively participating in the labor market. These results tie to our findings in the Table 3. Since employment-related activities mainly drive the baseline effect, the heterogeneous effect for active labor market participants is reassuring.

We also observe that the reduced time outdoors due to air pollution is driven by self-employed or casual laborers (Figure 3).[29,30] Respondents with these usual principal activity statuses spend significantly more time working outdoors than regular wage or salaried employees. Besides, they are more likely to have flexible work schedules so that they can adjust the labor supply decisions in the short-run. On top of that, we find no statistically significant effect for regular wage or salaried employees, for whom the point estimates are also smaller in magnitude. This is due to the absence of flexibility in short-run labor supply decisions for this subpopulation, which does not provide enough margin to reallocate time spent on employment-related outdoor activities, in addition to the fact that they spend less time working outdoors. Since employment activities drive the decline in time spent outdoors, the

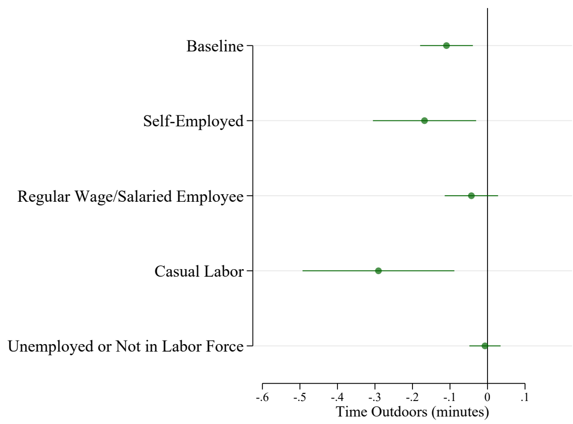
[27] To address this question, we change the estimating sample by creating four mutually exclusive and exhaustive groups with different age intervals. The first group consists of all respondents who are at least six but below 22 years of age. These are respondents who are most likely to be in school or college. The second group consists of respondents who are between the ages of 23 and 45 years. These respondents are actively participating in the labor market. The third group consists of respondents between the ages of 46 and 60. The final group consists of respondents who are above the age of 60. Point estimates and associated standard errors for these four age groups are reported in Table C17.

[28] We note that the effect on younger (age between 23 and 45) and older adults (age between 46 and 60) is not statistically different from each other (p-value: 0.857).

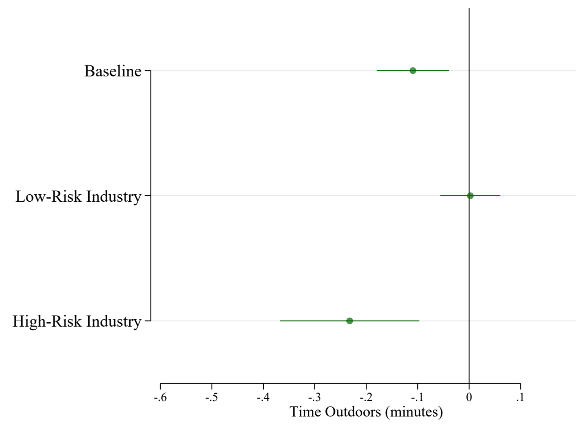
[29] Usual principal activity status contains information on whether the household member is employed, unemployed, or not in the labor force. For employed respondents, we construct three mutually exclusive and exhaustive groups - self-employed, regular wage or salaried employee, and casual laborer. We combine respondents who are unemployed or not in the labor force in a single group. We present point estimates and associated standard errors in Table C18.

[30] On examining whether the effect differs across respondents who are self-employed and casual laborers, we do not find a statistically significant difference (p-value: 0.324).

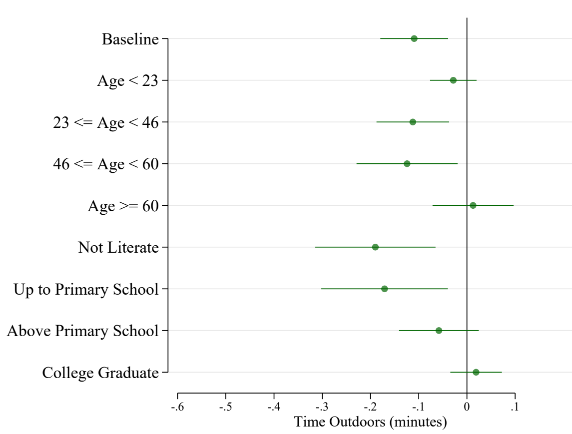
Figure 3: Heterogeneous Effects



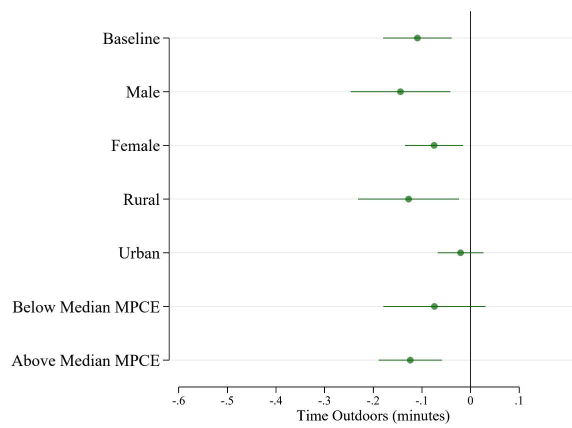
(a) Usual Principal Activity Status



(b) Industry Risk



(c) Age and Education



(d) Gender, Rural-urban status, and Usual Monthly Consumption Expenditure Per-capita

Note: The dependent variable on the horizontal axis is the marginal effect of the $PM_{2.5}$ concentration in $\mu g/m^3$ on time spent outdoors in minutes for the specific subpopulation. Vertical axis labels indicate the subpopulation. See the main text for a description of each subpopulation. Horizontal lines show 95% confidence intervals. Heteroskedasticity robust standard errors are clustered at the district-level. Each specification includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. Multiple activities in a given time slot are assigned equal time.

heterogeneity by usual principal activity status echoes our previous results.[31]

We also examine if high levels of air pollution in preceding days lead to respondents not reducing their time outdoors. As self-employed and casual laborers are unlikely to continuously miss work, high pollution levels in the immediately preceding days may dampen the negative influence of ambient air pollution on time outdoors. Estimates in Table C20 suggest that this is likely to be the case in our setting. In this table, time outdoors reduces if air pollution levels continue to be higher than the 2018 $PM2.5$ monthly concentration or two days and not thereafter. Together, the estimates in Table C20 show that reduction in time persists in short-run and progressively becomes weaker if air quality deterioration persists for multiple days.

Similarly, the findings differ by the risk of outdoor exposure of industries in which the respondents are employed.[32] We treat an industry to be high-risk if it is related to either agriculture, forestry, fishing and hunting, mining, construction, manufacturing, transportation, and utilities. The results show that the reduction in time spent outdoors is driven entirely by high-risk industry workers and absent for low-risk industries (Figure 3).[33,34]

On examining if the reduction in time outdoors is concentrated within certain days-of-week, we find that the decline in time outdoors is more pronounced at the beginning of the week.[35] However, the beginning of the week effect on time outdoors does not differ at conventional statistical significance levels from other days during the week. As the decline in outdoor time is concentrated within self-employed and casual wage labor respondents, the absence of differential effects by day-of-week is unsurprising as respondents with these usual principal activity statuses are likely to be outdoors on all days during the week. We highlight that this finding is in contrast to Connolly (2008) who find significant differences in time allocation across day-of-week. This point of departure from the existing work reflects the differences in the labor market structure of the two contexts.

Reduced time outdoors chiefly comes from employment-related activities outdoors (discussed in Section 4.3.1), and it is self-employed and casual laborers who drive the decline

[31]We find that if we drop the days with air pollution concentrations above the threshold where the construction activities are supposed to stop (Ganguly et al., 2020), our conclusions for differential effects by usual principal activity status are unaltered. These results are reported in Table C19.

[32]We use the information on the work industry for respondents who report being employed as their usual principal activity status to define an industry in which the respondent is employed as being high-risk or not. ITUS provides two-digit codes for the respondents' employment industry. We rely on the high-risk classification of industries in Graff Zivin and Neidell (2014).

[33]Point estimates and associated standard errors are presented in Table C21.

[34]In one of the specifications, we restrict the sample to retail or hospitality industries. These industries may be subject to short-run demand fluctuations due to ambient air pollution levels. In results available upon request, we do not find this to be the case.

[35]We restrict the estimating sample to those respondents who are interviewed on a given day-of-week. We present results in Figure C8.

in time outdoors. Therefore, it is likely that within these employment statuses, relatively richer households reduce time spent outdoors. Indeed, in Table C22 it is relatively richer respondents among the self-employed and casual laborers who reduce time outdoors. Taken together, these results suggest that the ability to afford a reduction in time outdoors is important to dampen pollution exposure.

Moreover, we find that the effect of air pollution exposure on time spent outdoors monotonically decreases as the respondent's level of education increases.[36] The most pronounced effect is found for illiterate respondents, whereas the effect is lacking for respondents who have completed college.[37] We interpret this finding against the backdrop of higher returns to college education compared to the returns to lower levels of education in the labor market. Besides, since college-educated individuals in our context are more likely to be employed in the formal sector with relatively more stringent working requirements, the absence of the effect for this subpopulation is anticipated.

Our main effect is also heterogeneous across other individual and household characteristics. We examine heterogeneity by gender, rural-urban status, and usual monthly per capita consumption expenditure (MPCE). We restrict the estimating sample based on the categories mentioned above. As shown in Figure 3, the effect is concentrated in the rural area residents rather than those residing in urban areas (p-value: 0.066).[38] While the point estimates by sex, wealth (above or below median MPCE), and dwelling structure differ across respondents, they are not statistically different from each other.[39] Moreover, the reduction in time spent outdoors does not significantly vary between households with and without dependents (Table C25).

4.3.3 Impact on Intrahousehold Gendered Distribution of Activities

We test if time spent on unpaid care outdoors is reallocated between male and female members of the households. We restrict the estimating sample to households with at least one

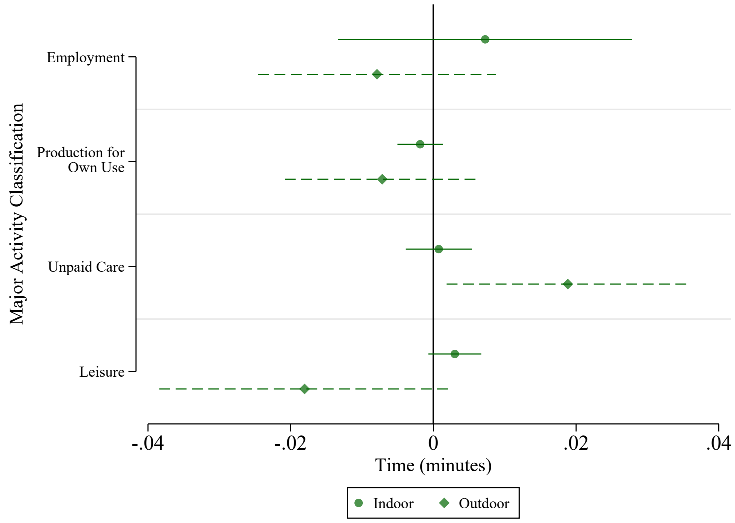
[36] We restrict our estimating sample to those above 23 years of age. These respondents are more likely to have completed their education. We construct four mutually exclusive and exhaustive groups of education levels of the respondents to examine if the effect of air pollution exposure on time spent on activities performed outdoors differs between these groups. The first group consists of respondents who are coded as being illiterate in the survey. ITUS considers a respondent to be literate if they can read and write a simple message with understanding in at least one language. The second group comprises respondents who have completed primary school education. The third and fourth groups consist of those respondents who have completed above primary school and college, respectively. We present the point estimates and associated standard errors in Table C23.

[37] For respondents who are designated as "illiterate" and "up to primary school", the effect is not statistically distinguishable from each other; however, these estimates are significantly different from the estimates for respondents having higher levels of education.

[38] ITUS defines rural and urban areas as inhabited villages and as towns/cities, respectively.

[39] Table C24 present results for "both major and minor activities" and "only major activities".

Figure 4: Male Share in Major Activity Classification



Note: The dependent variable on the horizontal axis is the marginal effect of the $PM_{2.5}$ concentration in $\mu g/m^3$ on male share of time spent in minutes on activities within the major activity classification. See the main text for which activities are categorized in these major activity classifications. Horizontal lines show 90% confidence intervals. Heteroskedasticity robust standard errors are clustered at the district-level. Each specification includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. Only those households that have at least one male and one female member are in the analytical sample. Male share in each activity type is the ratio of total time spent in that activity by male members to the total time spent in that activity by all members of the household. Multiple activities in a given time slot are assigned equal time. Point estimates along with standard errors are presented in Table C26.

male and one female member and construct a measure of male members' share of time spent on four broad groups of activities discussed previously for Table 3. Male share in each broad activity (discussed in Section 4.3.1) is the ratio of total time spent in that activity by male members to the total time spent in that activity by all members of the household. We estimate household-level specifications with the same set of weather controls and fixed-effects as those in Equation (1) - (3). The dependent variable now is the share of time male household members spent on various broad activity groups. We find that the share of time males spent on leisure outdoors goes down (see results in Figure 4).[40]

At the same time, we observe that the male share of time spent on outdoor unpaid care goes up. We exercise caution in interpreting these results as more gender-equal intrahousehold allocation of unpaid care as our estimates are sensitive to how the time in a given time slot is allocated between "major" and "minor" activities.[41] In Table C27 and Table C28, we show that the change in male share of the time spent on unpaid care activities is driven by a larger increase in time by male members than female members of the household on unpaid

[40] Associated point estimates and standard errors are reported in Table C26.

[41] In the top panel of Table C26, the time spent on activities other than "major" activities (or "minor") activities is also accounted for in each 30-minute interval. In the bottom panel of the same table, the entire 30-minute interval is assigned to the "main" activity associated with the time interval. For more discussion on these two ways of allocating time for the 30-minute intervals, see Section 2.1.

care activities. This suggests that what we document is an intrahousehold reallocation of unpaid care responsibilities between male and female household members, which is not driven solely by males increasing and females decreasing the time allocated to such activities.[42,43]

4.3.4 Is there an Intraday Reallocation of Time Outdoors?

We conclude this section by evaluating the within-day adjustment in time-use patterns. Since our pollution and weather conditions data varies within the day on which the time diary is recorded, we leverage this variation to study if the effects highlighted above differ significantly within a day. To this end, we replicate our main findings in Tables C31 - C36 and present estimates for three time intervals: 7:00 to 13:00, 13:00 to 19:00, and 19:00 to 7:00.

The point estimates in these tables reveal that our findings are driven by adjustments made in the first two intervals, i.e., during the daytime. This is expected as our main effect is driven by reduced time outdoors on employment-related activities, and such activities are most likely to be performed during these hours. We highlight one important result in these tables: Table C33 depicts that the time spent on indoor activities related to unpaid care goes up. This lends extra credence to our conclusion that reduced time indoors might lead to a more equitable distribution of unpaid care activities within the household.

4.4 Mechanisms

What drives the observed changes in time-use patterns on more polluted days? As Barwick et al. (2024) and Wang and Zhang (2023) show, information provision might lead to affected residents undertaking actions to reduce their air pollution exposure. We test whether more localized air quality information leads respondents to reduce their outdoor time more.[44] Our

[42]This effect is not driven by spillover to unmarried household members. In Table C29, we restrict the estimating sample to currently married household head and their spouse. We find that within these households, reallocation of time across male and female household members is similar to our main estimating sample without this restriction.

[43]To the extent that there is an intrahousehold reallocation of outdoor unpaid care activities, we should see a relatively larger decline for single-member households in baseline effect since the offset due to the time spent outdoors for unpaid care is non-existent for single-member households. We find that the decline in time spent outdoors is larger for single-member households than for households with multiple members. These results are presented in Table C30.

[44]We obtain information on the ground monitors that measure $PM_{2.5}$ concentrations from the Central Pollution Control Board (CPCB), Ministry of Environment, Forest and Climate Change, Govt. of India Central Control Room for Air Quality Management. We then classify a respondent as residing in a district with an air pollution monitor if their residence district or the adjacent district has at least one operating air pollution monitor. Air pollution levels in districts with ground-based monitors are frequently reported in the media and might be a channel through which residents acquire information on ambient air quality. We present results in Table C37.

point estimates suggest that the effect of air pollution exposure on time spent outdoors is more pronounced for residents of the districts that have a local ground-based air pollution monitor. This effect, however, is not statistically different from the effect for residents of the districts that do not have a proximate ground-based air pollution monitor (p-value: 0.648). Not every district in India has these monitors, and existing monitors provide intermittent information about air quality due to frequent outages. Further, the way better air quality information is measured in this case is just one of the multiple ways through which information on air quality can be disseminated. Figuring out the most cost-effective method of providing such information is a fruitful area for future research.

Nonetheless, information provision by external sources is not the only mechanism that constitutes the list of possible factors linking pollution exposure to the reallocation of time across activities. Air clarity and direct health effects play an important role when deciding whether to stay within indoor premises on highly polluted days. Indeed, visibility also serves as an immediate and intuitive form of information, readily apparent to the eye without necessitating additional verification from external sources.

Existing studies have also considered health impacts as the primary channel through which causal effects manifest, including contexts where information is provided. Rational individuals, informed or seasoned by experience, typically prioritize concerns regarding their health (and the well-being of their close ones) upon receiving news about pollution levels, thereby underlining health as the primary pathway.

In this regard, extremely high $PM_{2.5}$ levels should cause relatively more drastic deterioration in health conditions and more visual impairment, consequently leading to a higher magnitude in the estimates. Results in Table C38 suggest that progressively higher levels of air pollution lead to a more pronounced reduction in time outdoors.[45]

Given the discussion that higher levels of air pollution might lead to impaired visibility (Won et al., 2021), in Table C39, we establish that high particulate matter concentrations in the district lead to reduced visibility.[46] Thus, on more polluted days, residents may be induced to limit outdoor activities through perceptible changes in the atmospheric conditions, such as a buildup of haze and mist. Figure C10 finds that worse visibility is indeed associated with reduced time outdoors. This conclusion diverges from Wang et al. (2022) who in their analysis of ozone pollution's impact on worker productivity in China observed no change in couriers' avoidance behavior, attributing this absence of effect to the invisibility of ozone pollution.[47] Taken together, due to elevated air pollution levels, respondents may be reducing

[45]We modify specifications in Equations (2) - (3) by replacing the continuous and linear measure of $PM_{2.5}$ with an indicator for pollution to be higher than multiple $PM_{2.5}$ concentration thresholds.

[46]Figure C9 presents raw correlation between air pollution concentration and visibility.

[47]Using data on workers in an Indian ready-made-garment firm, Adhvaryu et al. (2022) find that one SD

time outdoors as deteriorated air quality provides visually perceptive evidence of high air pollution levels.

Additionally, due to the data limitations, we are unable to test the deterioration in health conditions directly as the pathway for the causal impact of air pollution on time-use patterns.[48] We further rely on existing literature about the effect of air pollution on health (Brewer et al., 2023). Hence, the combination of our analysis and existing literature demonstrates the role of direct health consequences and visibility deterioration as potential causal pathways leading to reduced time outdoors. We also acknowledge that health and visibility-related channels can have implications for labor productivity that may constitute another reason for the decline in time spent on outdoor employment. Such an explanation would be consistent with the fact that the impacts we find are concentrated in rural areas where, as shown by Merfeld (2023), air pollution can hamper agricultural productivity.

5 Discussion and Conclusion

We examine if and how air pollution exposure affects time reallocations across various indoor and outdoors activities using a nationally representative data on time-use from India. We then construct a measure of air pollution exposure using satellite reanalysis data on $PM_{2.5}$ concentrations and leverage changes in local wind directions in an instrumental variable setup to uncover the causal effect of air pollution exposure on time-use patterns. Our estimates suggest that one standard deviation (SD) increase in $PM_{2.5}$ concentration reduces time spent on outdoor activities by 0.04 SD (a decline of approximately eight minutes spent outdoors, or a 5.1% decline over the sample mean).

The effects are heterogeneous across subgroups and broad categories of activities: the results are more pronounced for rural area residents. Almost all of the decline in time outdoors results from the decline in time spent on employment outdoors and is driven by adjustments made in the activities performed during the daytime. Then, this time saved from

increase in $PM2.5$ decreases worker productivity by approximately 1.6% relative to the sample mean. While productivity is not the central measure of our work, it is plausible that a decline in productivity could be a pathway through which the reduced time outdoors manifests. The decline in productivity could itself result from worsened cognitive and physical performance emanating from health deterioration when air quality worsens.

[48] In Table C40, we show that the time spent on activities related to health does not change significantly on exposure to elevated levels of air pollution. However, we note that our main estimating sample is restricted to those who are 18 to 60 years of age. In Table C40, we test if the time spent on activities related to health goes up for the relatively more vulnerable subpopulation (age between six and 22 years). The point estimates in this table confirm that the worsening of health in the vulnerable subpopulation might be a channel through which reduced time outdoors results. This could happen, for instance, if the adult members of the households are required to take care of household members in these age groups.

employment is reallocated to leisure-related indoor or unpaid care-related outdoor activities.

The elevated levels of air pollution might lead to more equitable intrahousehold distribution of activities related to unpaid care. Notably, we find that on more polluted days, the share of male members' time allocated to unpaid care activities outdoors increases. This finding assumes a greater weight in a developing country setting like India, where the burden of such activities often disproportionately falls on female members of the household (Deshpande and Kabeer, 2024). However, such potentially unintended benefit of elevated pollution levels might come at significant monetary costs due to lost earnings to the extent that the reduced time outdoors emanates from reduced labor supply.

There could be multiple channels through which air pollution exposure may trigger the changes in time-use patterns. It might be the case that exposure worsens health, and exposed residents are incapacitated, reducing their time outdoors. Lastly, perceptible changes in air pollution levels, like reduced visibility, affect how people allocate their time. We find support for visually perceptible changes in air quality as a channel through which the time reallocation across activities emerges, although we cannot rule out the potential effect through health and productivity.

How do our effect sizes compare to the existing works examining the effect of contemporaneous air pollution exposure on labor market outcomes? Focusing on the metropolitan area in Mexico City, Hoffmann and Rud (2022) document a 8.928 minute decline in same-day work time due to a one SD increase in daytime $PM2.5$ above 75 $\mu g/m^3$. While slightly small, our point estimates equate to a decline in employment time outdoors equivalent to 7.80 minutes on account of one SD increase in $PM2.5$ concentration. Focusing on the labor market in the United States, Borgschulte et al. (2022) estimate a 0.125 percent decline in labor force participation relative to the sample mean due to a one unit increase in $PM2.5$ concentration. Our estimates translate to a decline of 0.106 percent in employment time outdoors relative to the sample mean due to a one-unit increase in $PM2.5$ concentration.

In a meta-analysis of existing work examining labor market outcome changes due to air pollution, Borgschulte et al. (2022) estimate an implied elasticity of -0.18. Our estimates suggest that this implied elasticity in our setting is -0.08 for employment outdoors.[49] This suggests that in a setting with high informality in the labor market along with nonexistent employee protections, the labor market response to air pollution is dampened.

To quantify the marginal willingness to pay (WTP) for air quality improvements, we refer to the World Health Organization (WHO) 24-hour safe $PM2.5$ limit of 15 $\mu g/m^3$ (WHO,

[49] This estimate is calculated as following: $(-0.106) \times \frac{83.982}{99.663}$. In this calculation, -0.106 is the marginal effect of one unit increase in the $PM2.5$ concentration from Table 3 on employment time outdoors, 83.982 is the average $PM2.5$ in our analytical sample from Table C4, and 99.663 is the average employment time outdoors from Table 3.

2021). Recall that the reduced time outdoors stems from activities related to employment that are performed outdoors (Table 3). Furthermore, the decline in time outdoors is concentrated in respondents whose usual principal activity status (UPAS) is either self-employment or casual labor (see column (1) and (3) of Table C18) and who reside in rural areas (see column (3) of Table C24). Assuming the linearity of the dose-response function for the time reallocation, an employed respondent is WTP almost 7.34% of their daily wages on average to improve air quality to a level that is considered safe according to the WHO standards.[50] When disaggregating the WTP measure by sex of the respondent, we estimate WTP for female and male respondents of 8.31% and 4.77%, respectively.[51]

We use wage data from the Periodic Labor Force Survey (PLFS) 2017-18 to monetize these lost wages due to air pollution. Since the decline in time spent on outdoor activities is concentrated in the rural areas and among those respondents whose UPAS is either self-employment or casual labor, we use wage data for these subgroups.[52] Using these wage estimates together with the size of these groups in the overall labor force, we estimate at least $61.22 million in lost daily wages on average in the overall population due to air pollution concentration being more than the WHO-safe levels.[53]

Our results have major implications for the behavioral responses of residents of developing countries that contend with very high air pollution levels, many of whom do not have access to affordable technologies to limit their exposure to air pollution. In the absence of such technologies, they rely on costly adjustments by reallocating their time, often by reducing their labor supply and forgoing significant earnings. Though data precludes analyzing relatively lower ambient pollution levels indoors, such air pollution disparity between indoors and outdoors might be the primary reason to reduce time outdoors.

Since there are other margins over which the residents limit their air pollution exposure, our findings might be interpreted as the lower bound estimates of avoidance behavior. With-

[50] The calculation is as follows: $\frac{(83.982-15)*(-0.106)}{99.663} \approxeq -0.0734$. In this calculation, 83.982 is the sample average $PM2.5$ concentration, as documented in Table C4. -0.106 is the marginal effect of a one microgram per cubic meter increase in $PM2.5$ concentration on outdoor activities related to employment (see column (5) of Table 3). Finally, 99.663 is the average time spent on employment-related activities outdoors.

[51] In Table C41, we establish that the decline in time outdoors for female respondents is concentrated only in UPAS casual labor. For the male respondents, air pollution leads to a decline in time outdoors for both self-employed and casual labor UPAS. The WTP measure for each sex is calculated using the approach in footnote 50.

[52] The estimated average daily wage for casual laborers in rural areas is 246 rupees (Table 43 of PLFS Annual Report), and for self-employed, it is 281 rupees (Table 45 of PLFS Annual Report).

[53] From Table 32 in the PLFS Annual Report, we obtain an estimated number of people in the rural areas whose UPAS is either self-employed (146,062,700) or casual laborer (75,513,300). We then average the daily wage for those who report their UPAS as either self-employed or casual laborers. We take an exchange rate of 70 rupees for each USD to convert the rupee value to US dollars. Therefore, this calculation is given as: $((1460627 + 755133) * 100) * \frac{0.0734 * \frac{246+281}{2}}{70}$.

out ambient air quality improvements, the adjustment margin documented might become more important. This is the case when the availability of cheap air purification technologies widens the disparity between indoor and outdoor air quality, which might induce residents to spend more time indoors.Further, by reducing their time outdoors, residents of highly polluted regions might also suffer from deleterious health effects due to inactivity, over and above the widely documented negative health effects of air pollution exposure.

Our work has several limitations. Our sample is from before the COVID-19 pandemic; given the widespread adoption of remote work, we are unable to examine if the effects on regular wage or salaried employees have changed over time. Furthermore, we highlight the short-run intensive margin of labor supply decision in the wake of transitory air pollution shock. Our data precludes us from investigating extensive margins of industrial or occupational choice.[54] Identifying these and other margins of adjustment due to air pollution exposure may constitute a future area of research.

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Appendices

Appendix A Analytical Sample Construction

This section describes how we combine survey data on time-use and satellite reanalysis data on air pollution levels and weather conditions. To combine these distinct sets of data, we perform a matching exercise using districts as the spatial units. We use information on the district of residence for the household in the ITUS data. The district is the finest geographical unit that we observe in ITUS.[55]

To construct district-level measures of air pollution concentrations and weather conditions, we use district-level shapefiles extracted from the Housing and Population Census of 2011. It should be noted that ITUS data were collected in 2019, whilst many new districts have formed since 2011 by collapsing previous states or districts. In order to obtain information on all districts in the ITUS data, we manually determined the parent district in 2011 shapefiles data for each district that was newly created between 2011 and 2019. Therefore, we can construct measures of air pollution and weather conditions for each district that we observe in ITUS data.

We construct measures of each pollutant by weighting each grid that intersects the district polygon by the extent of its overlap. We do this for each time layer observed in the CAMS EAC4 data. In order to construct the air pollution measures relevant to the 24-hour time period over which the activities are recorded, we take the average of the eight three-hour measures in the relevant 24-hour period. Therefore, we create a daily measure of air pollution concentrations for each of our pollutants. We follow a similar scheme to construct weather measures from ERA5-Land data, whereby the only difference is that we average all 24 hourly measures within the relevant ITUS 24-hour time period.

Finally, we combine the daily measures of air pollution and weather conditions at the district-level with the ITUS data using the information on the district of residence of the household. It should be noted that we do not have survey data information for 951 households, which prevents obtaining pollution exposure for these households. Therefore, in our analysis, we drop observations on these households.

[55] Average district is comparable in size to an average county in the United States of America.

Appendix B Identification Strategy

In this section, we expand on the instrumental variables (IV) setup that we use to identify and estimate the causal effect of air pollution exposure on time-use patterns. We first discuss the construction of the instrumental variables followed by a discussion of identifying assumptions for our IV estimates to be interpreted causally. Then potential threats to these assumptions are discussed. Finally, we discuss various falsification exercises that we conduct to assuage concerns about the validity of the IV estimates. We note that our IV setup is borrowed from Deryugina et al. (2019).

We instrument for district-level air pollution concentrations with the interaction of the district to be in one of the many geographical clusters and district-level wind direction, which we discretize to be in one of the twelve 30° bins. For classifying the districts to be in one of the many geographical clusters, we use the k- means clustering algorithm. This algorithm classifies geographical proximate districts based on their centroid together. For our baseline specifications, we restrict the number of clusters to 40.

Figure C5 presents these clusters. However, in Table C5, we establish the robustness of our main results to changing the number of clusters. Ideally, we would like each district to be its own cluster, but this is computationally burdensome. For our baseline specifications, we use twelve 30° bins to classify the wind direction. We potentially lose meaningful variation by using the large bin. However, using more wind direction bins increases the computational demands without significantly altering the main findings of the paper.

To identify the causal effect of air pollution exposure on time allocation, the instruments should affect time-use patterns only through their effect on air pollution concentration. It is not evident if a particular wind direction should systematically affect time-use patterns except through its effect on air pollution levels. This exclusion restriction assumption is inherently untestable, we later discuss multiple empirical tests that increase confidence in the validity of our IV setup.

Since the wind direction affects air pollution concentrations in all districts in a given cluster similarly, we do not rely on the information on the location of local polluting sources. Therefore, in our setup, we do not leverage changes in air pollution levels that local polluting activities might drive. This helps address endogeneity concerns related to the local time-varying unobservables that jointly affect time-use patterns and air pollution levels.

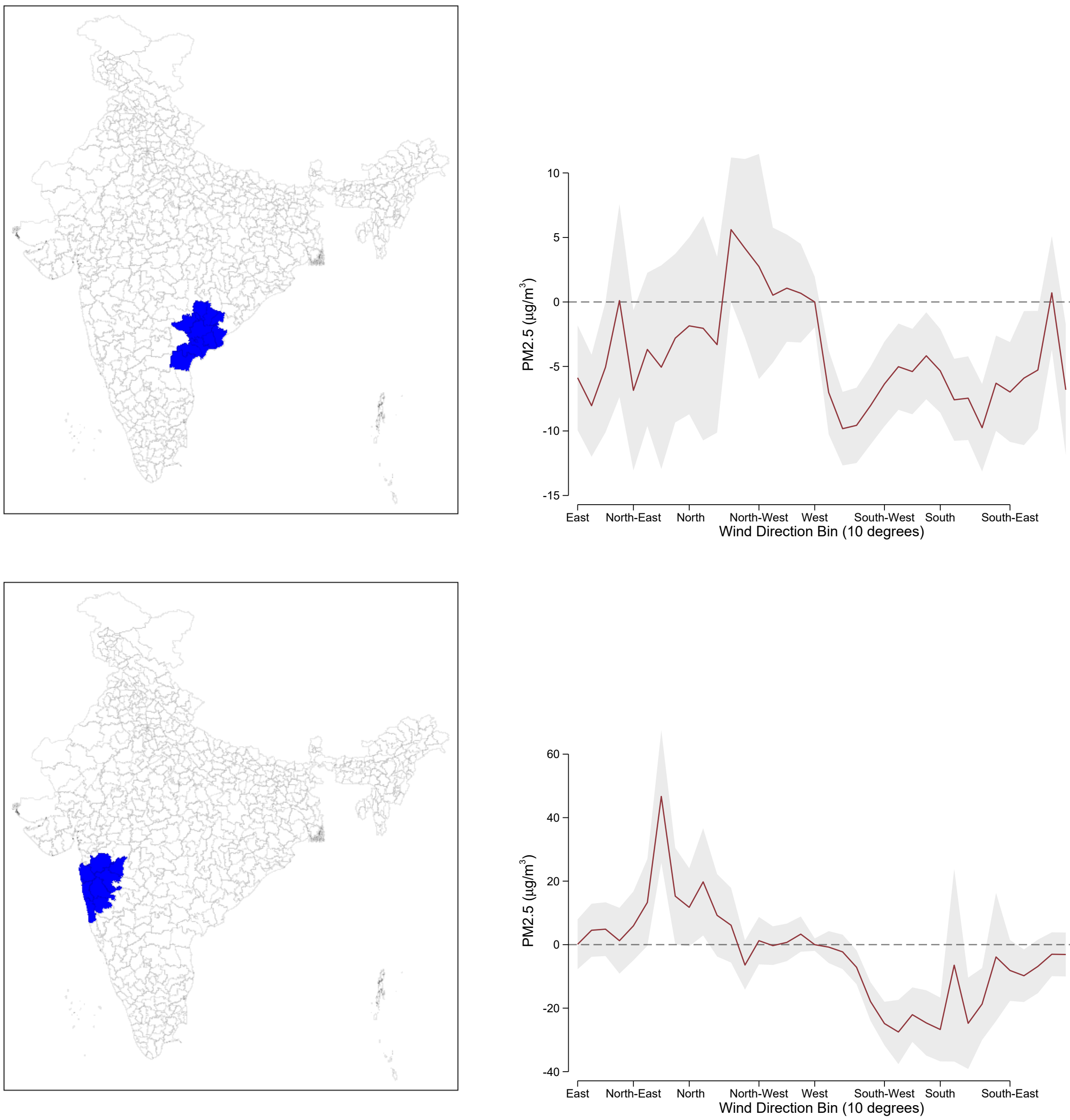
Figure B1 presents the identifying variation that we use to estimate the causal effect of air pollution exposure on time-use patterns. We note that the width of the wind direction bin in this figure is 10 degrees. We present two distinct clusters where the same wind direction exerts very different influences on pollution concentrations. For instance, relative to wind from the west, wind from the east decreases pollution levels in the top cluster but has no significant effect on the air pollution levels in the bottom cluster.

Since we do not have the precise location of residence of respondents in the time-use survey data, our pollution exposure measure is constructed at the district-level as that is the finest spatial unit on which the information is available in the survey data. This exposure measure might induce some measurement error in the respondents' exposure to pollution. However, our IV strategy can mitigate this concern. Since we force a wind direction to affect the air pollution similarly for all districts within the cluster of districts, we essentially leverage the change in air pollution concentrations driven by non-local distant polluting sources.

As direct evidence for this, results in Table C5 suggest that our main estimates are not sensitive to either increasing or decreasing the number of districts in a cluster. If the majority of the variation in air pollution concentration is driven by local polluting sources, our estimates should be sensitive to the number of clusters used to classify districts. Reassuringly, we do not find this to be the case (p-value: 0.44).

Furthermore, we find that our instrument predicts the air pollution concentrations more strongly on days when the wind speed is the highest. In particular, the F-statistic for our first-stage estimation is almost four times as large when the wind speed is above the median of the empirical distribution of wind speed relative to when the wind speed is below the median of the empirical distribution of wind speed. This is strong evidence that non-local sources drive the identifying variation that we leverage.

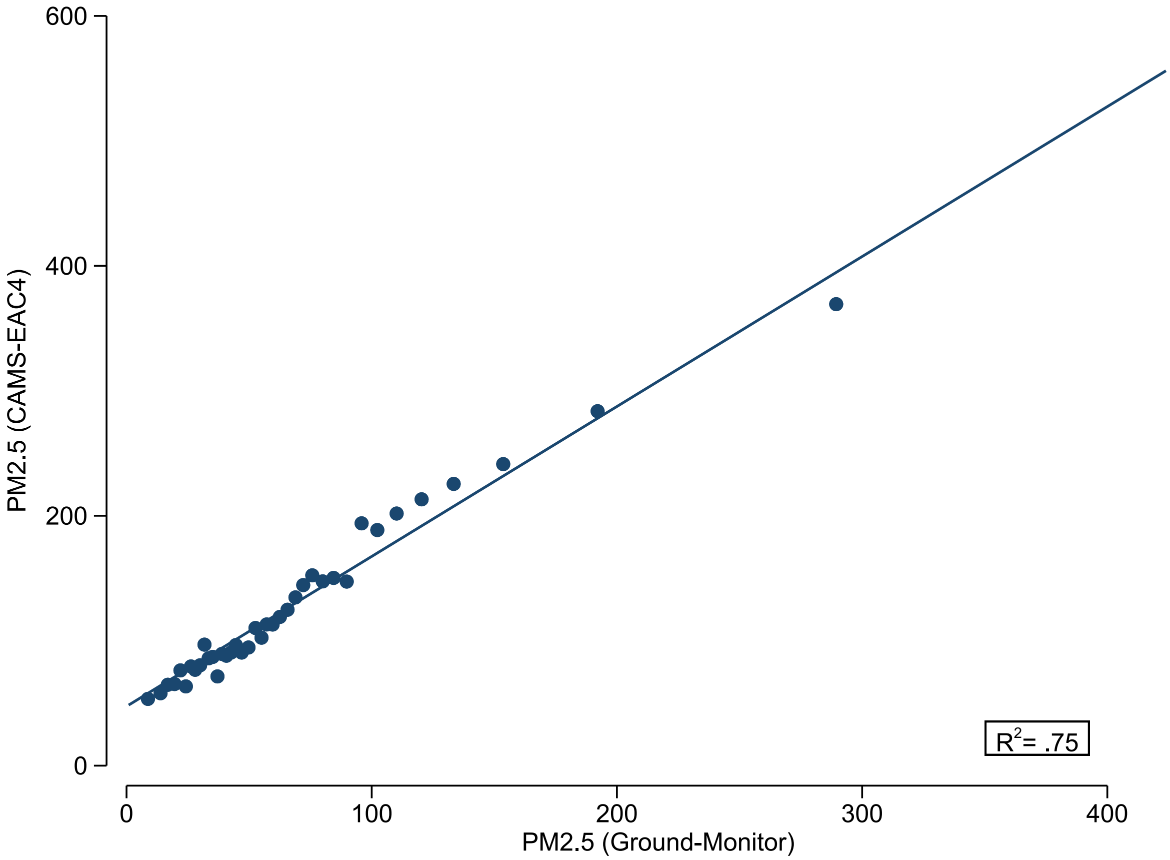
Figure B1: Instrument Motivation



Notes: This figure shows two distinct clusters of districts. The panels on the right plot regression estimates from an equation where the dependent variable is the daily $PM2.5$ concentration in the district, and the independent variables of interest are a set of indicators for the daily district wind direction falling in a particular 10-degree wind direction bin. This regression specification also controls for temperature and precipitation along with district and state-by-month fixed-effects. The panels on the right suggest that the same wind direction influences air pollution levels differently for these two clusters. For instance, relative to wind from the west, wind from the east decreases pollution levels in the top cluster but has no significant effect on the air pollution levels in the bottom cluster.

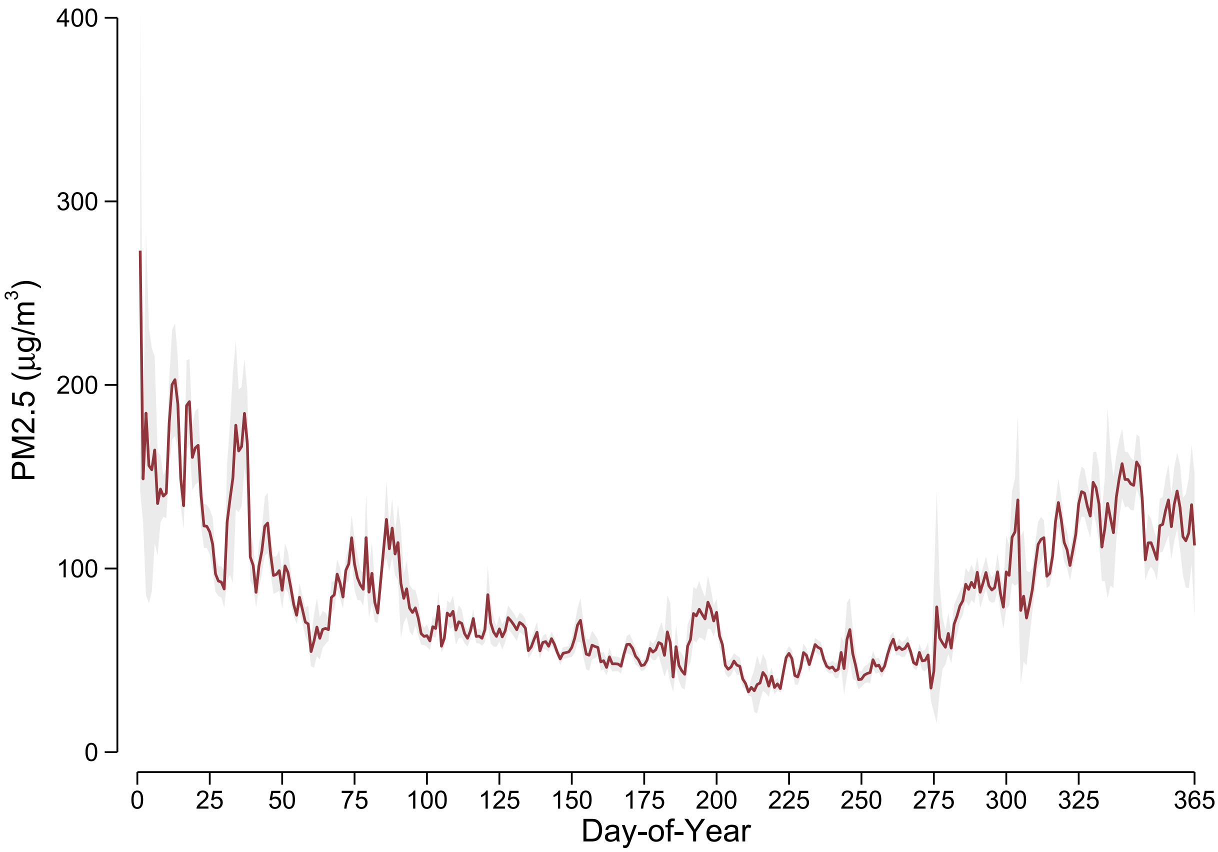
Appendix C Figures and Tables

Figure C1: Correlation between Ground Monitor and CAMS-EAC4 Data



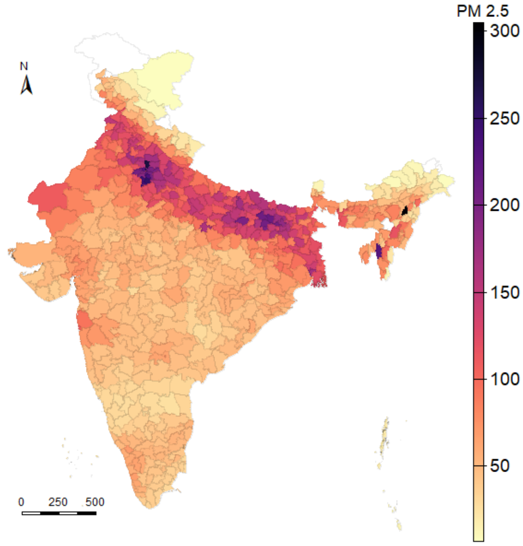
Note: Data for ground monitor $PM_{2.5}$ concentration comes from the Central Pollution Control Board (CPCB), Ministry of Environment, Forest and Climate Change, Govt. of India Central Control Room for Air Quality Management. CAMS-EAC4 data is provided by the European Centre for Medium-Range Weather Forecasts (ECMWF). R^2 is from regressing CAMS-EAC4 $PM_{2.5}$ concentration level on ground-monitor $PM_{2.5}$ concentration level. Both data series are defined at the daily level. The data is for all the days that are observed in the India Time Use Survey (ITUS) 2019. Only districts that have a ground monitor are part of the estimating sample. For multiple monitors within the districts, air pollution concentration levels are averaged across all the ground monitors using arithmetic mean.

Figure C2: Temporal Variation in $PM_{2.5}$ Concentration

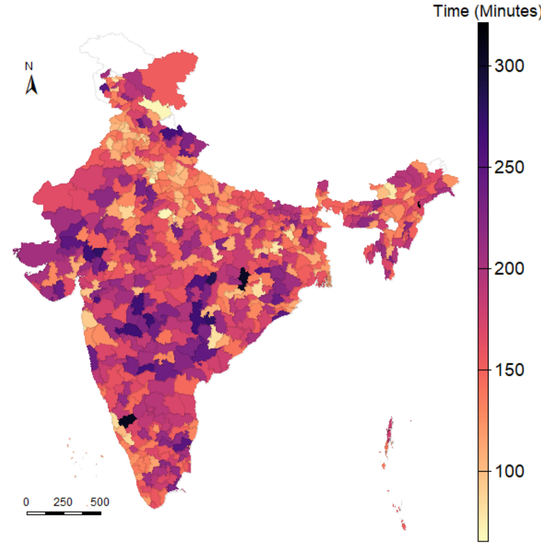


Note: Data on $PM_{2.5}$ concentration comes from CAMS-EAC4 satellite reanalysis data provided by the European Centre for Medium-Range Weather Forecasts (ECMWF). The mean $PM_{2.5}$ concentration across all districts for each day of the year, along with the 95% confidence interval, is plotted. Observations from 2019 are used.

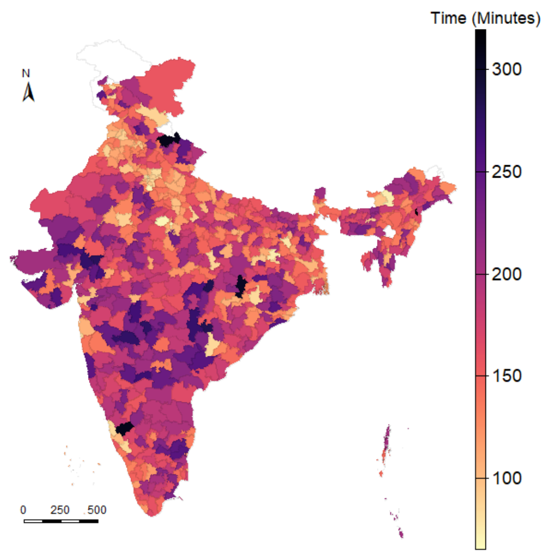
Figure C3: Spatial Variation in $PM_{2.5}$ Concentration and Time Outdoors



(a) Air Pollution Concentration $PM_{2.5}$ $\left(\mu g/m^3\right)$



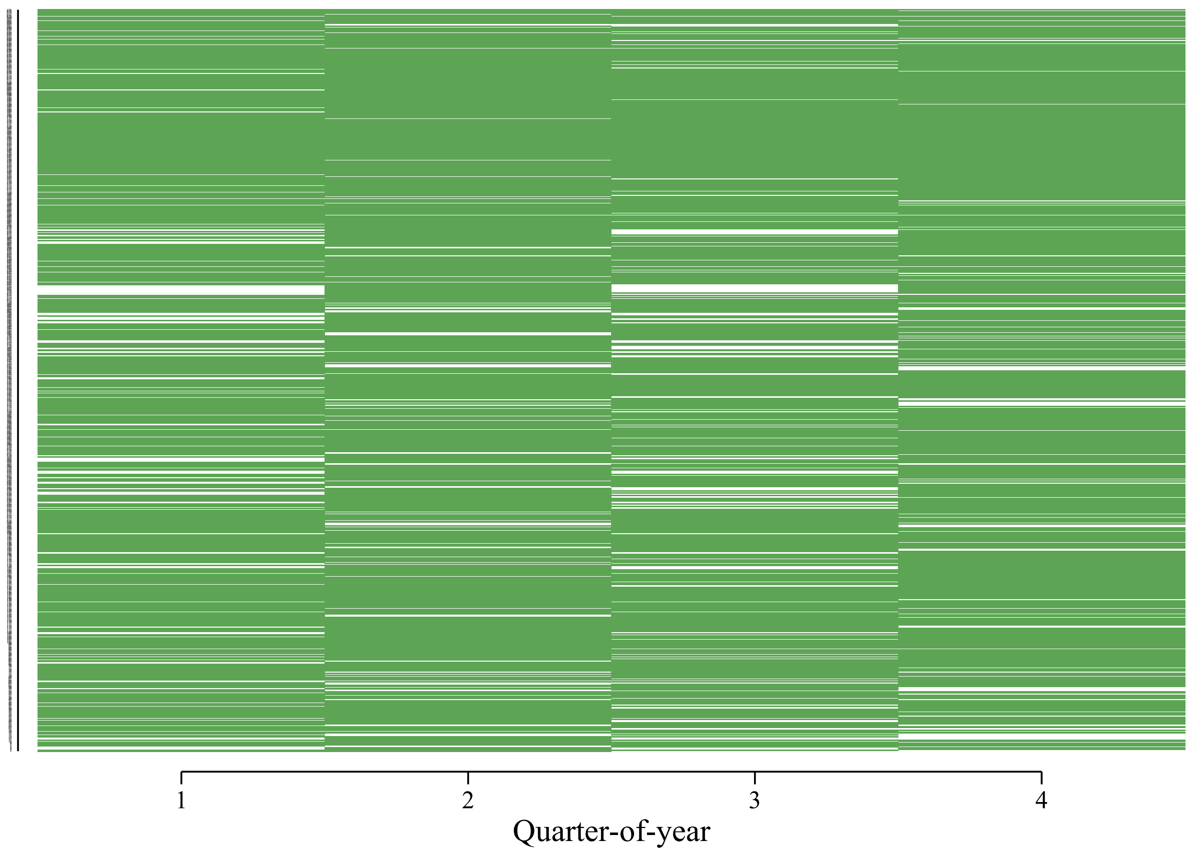
(b) Time on Outdoor Activities: Both Major and Minor Activity



(c) Time on Outdoor Activities: Only Major Activity

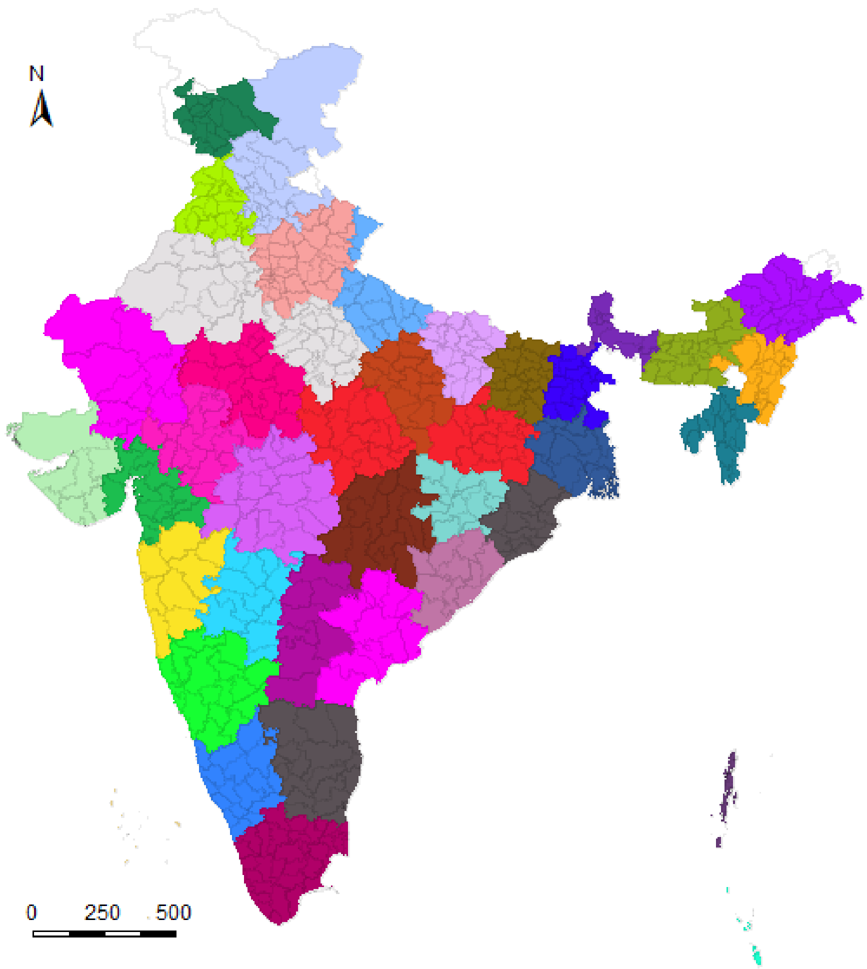
Note: Data on $PM_{2.5}$ concentration comes from CAMS-EAC4 satellite reanalysis data provided by the European Centre for Medium-Range Weather Forecasts (ECMWF). $PM_{2.5}$ concentration is averaged over all the days on which at least one interview is conducted in the district using arithmetic mean. Time on outdoor activities in panels (b) and (c) is in minutes. Time on outdoor activities is averaged for all the respondents in a given district using arithmetic mean. Panel (b) uses time division where the time on all activities in the time interval is distributed equally among the activities in that time interval. Panel (c) allocates time in a given time interval only to the "major" activity reported by the respondent for that time interval. See the main text for details on time divisions. The district polygons come from the 2011 Census of India.

Figure C4: Any Interview During the Quarter of Calendar Year



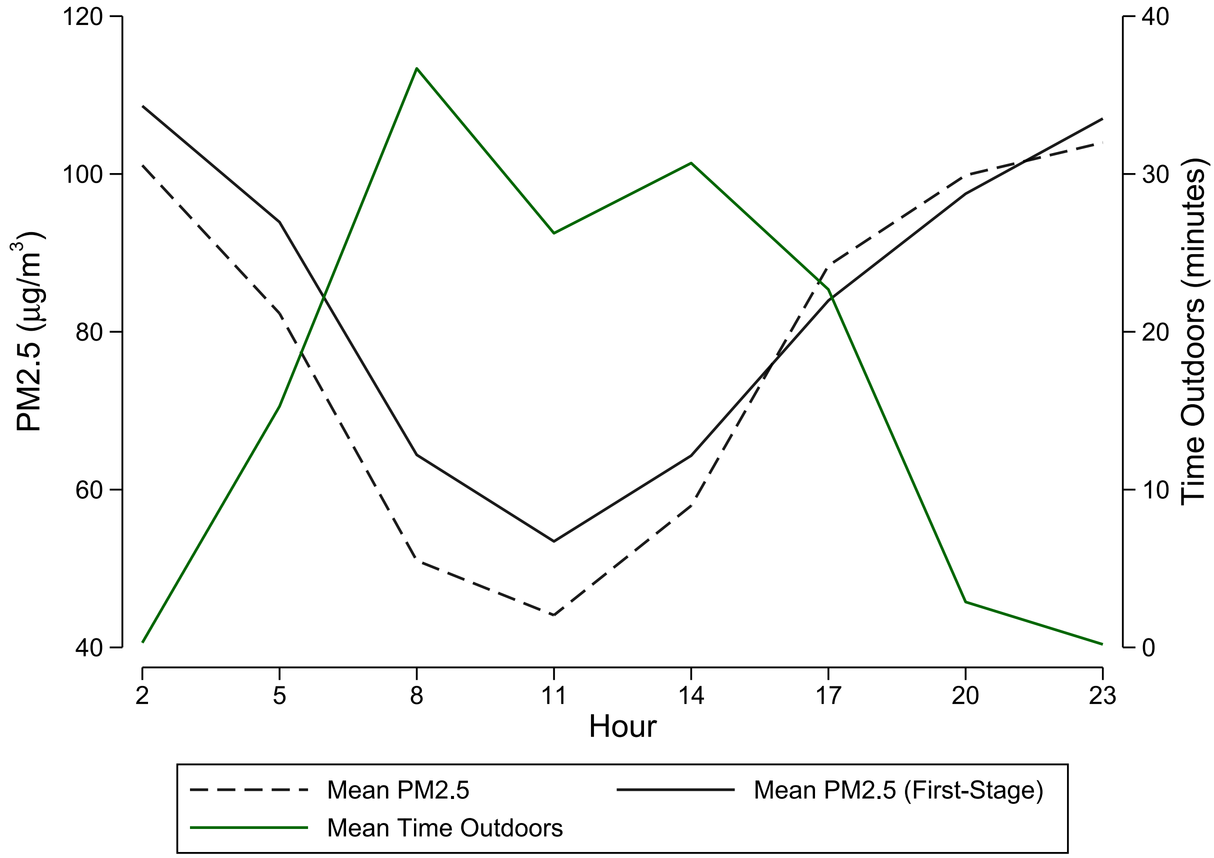
Note: Data on Interviews are from the India Time Use Survey (ITUS) 2019. The vertical axis denotes the district identifier. The horizontal axis is the quarter of the calendar year. Quarters with white fill do not have any interviews conducted during that quarter in the district. The green fill quarters have at least one interview in the district during that quarter.

Figure C5: District Clusters



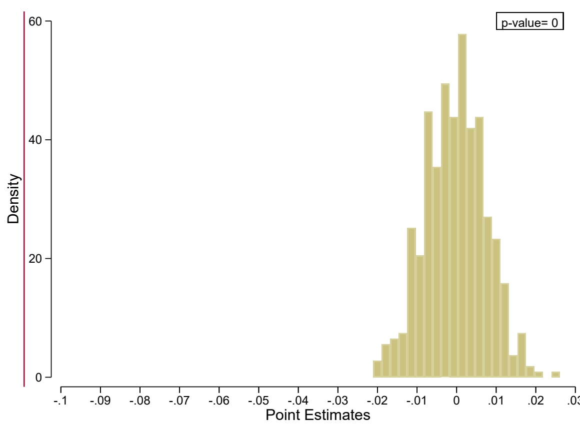
Note: Districts are classified into 40 distinct clusters using the k-nearest neighbor algorithm. District centroid longitude and latitude are used for classification. The district polygons come from the 2011 Census of India.

Figure C6: Intraday Variation in $PM_{2.5}$ Concentration and Time Outdoors

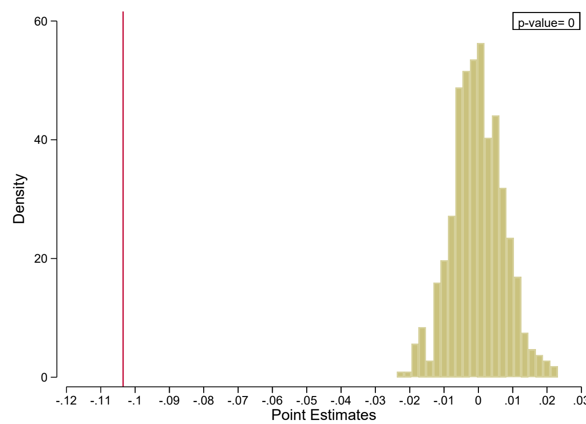


Note: Data on $PM_{2.5}$ concentration comes from CAMS-EAC4 satellite reanalysis data provided by the European Centre for Medium-Range Weather Forecasts (ECMWF). The arithmetic mean of $PM_{2.5}$ concentration and time outdoors across all districts and days in the sample for each three-hour interval, is plotted.

Figure C7: Placebo Check: Randomization Inference



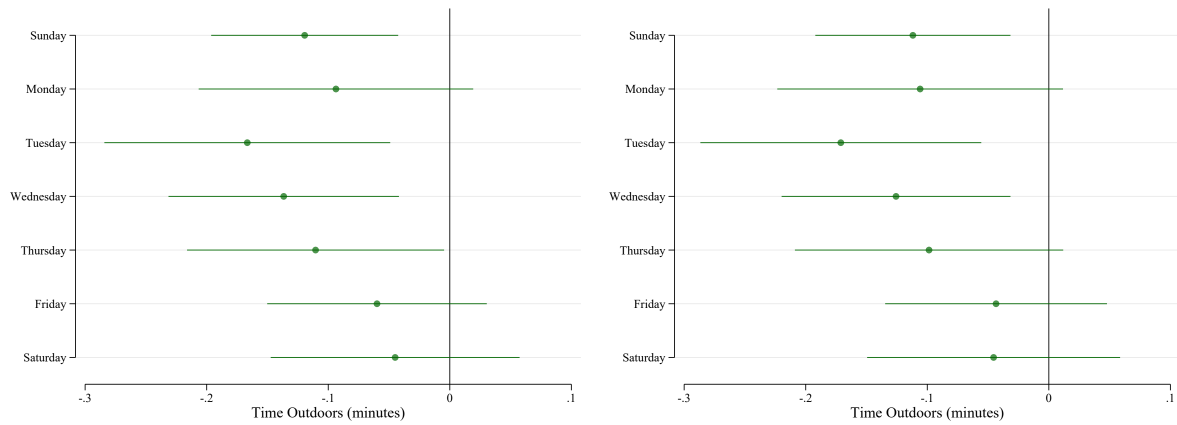
(a) Both Major and Minor Activity



(b) Only Major Activity

Note: The histogram of the point estimate on the $PM_{2.5}$ concentration variable is plotted. $PM_{2.5}$ concentration and weather controls are randomly permuted for the estimating sample. This process is repeated 500 times. The vertical line in each panel corresponds to the baseline point estimate. p-value is the proportion of the placebo point estimates that are less than baseline point estimates. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The dependent variable for all specifications is the amount of time spent on outdoor activities in minutes. Activities classified as outdoor are discussed in the main text. Each specification includes weather controls, district, and day-of-year fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables in IV specifications are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Figure C8: Heterogeneity by the Day-of-Week

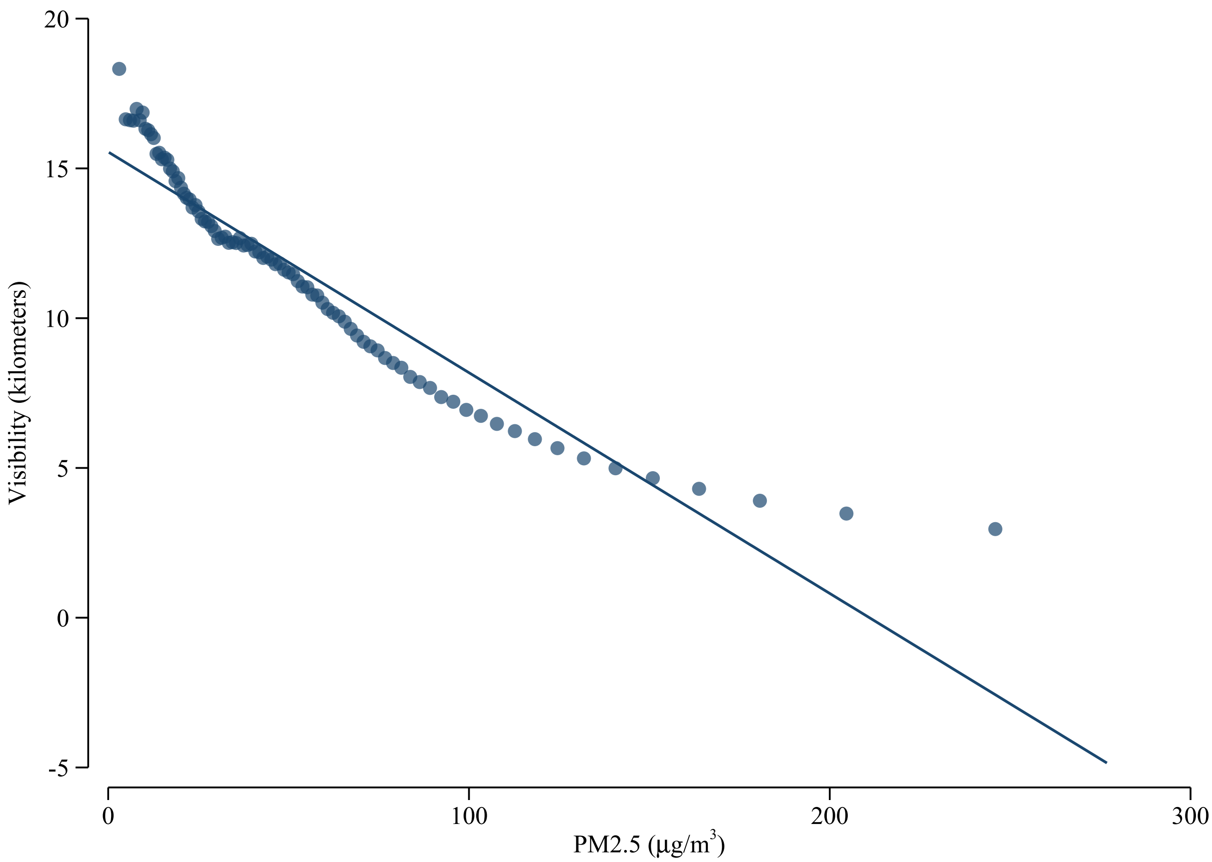


(a) Both Major and Minor Activity

(b) Only Major Activity

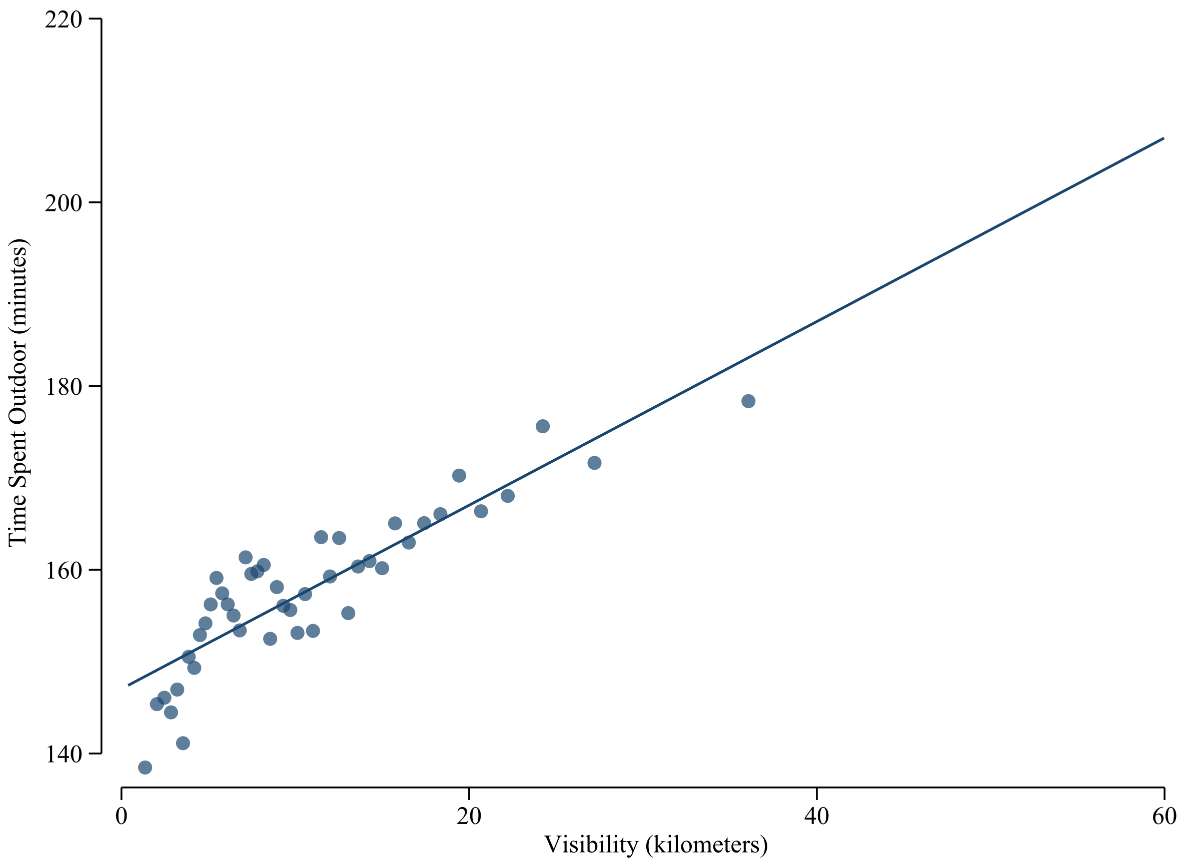
Note: Point estimates on the $PM_{2.5}$ concentration variable are plotted on the vertical axis. Heteroskedasticity robust standard errors clustered by the district are used to construct the confidence intervals. Vertical lines show 95% confidence intervals. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The dependent variable for all specifications is the amount of time spent on outdoor activities. Activities classified as outdoor are discussed in the main text. The day of the week which forms part of the estimating sample is noted at the bottom of each panel. Each specification includes weather controls, district, and day-of-year fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables in IV specifications are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019. The horizontal line in each panel corresponds to zero.

Figure C9: Correlation between Visibility and Air Pollution



Note: Data on $PM_{2.5}$ concentration and visibility comes from CAMS-EAC4 satellite reanalysis data provided by the European Centre for Medium-Range Weather Forecasts (ECMWF). The figure plots the binscatter least square estimates derived using the methods in Cattaneo et al. (2023). The degree of global polynomial regression is set to one.

Figure C10: Correlation between Time Outdoors and Visibility



Note: Data on time spent outdoors is from the India Time Use Survey (ITUS) 2019. Data on visibility comes from CAMS-EAC4 satellite reanalysis data provided by the European Centre for Medium-Range Weather Forecasts (ECMWF). The figure plots the binscatter least square estimates derived using the methods in Cattaneo et al. (2023). The degree of global polynomial regression is set to one.

Table C1: Three-Digit Code and Description of Activities Classified as Outdoors

Three-Digit Code	Activity Description
121	Growing of crops for the market in household enterprises
122	Raising of animals for the market in household enterprises
123	Forestry and logging for the market in household enterprises
124	Fishing for the market in household enterprises
125	Aquaculture for the market in household enterprises
126	Mining and quarrying for the market in household enterprises
128	Construction activities for the market in household enterprises
134	Transporting goods and passengers for pay or profit in households and household enterprises
181	Employment-related travel
182	Commuting
211	Growing of crops and kitchen gardening for own final use
212	Farming of animals and production of animal products for own final use
213	Hunting, trapping and production of animal skins for own final use
214	Forestry and logging for own final use
215	Gathering wild products for own final use
216	Fishing for own final use
217	Aquaculture for own final use
218	Mining and quarrying for own final use
230	Construction activities for own final use
241	Gathering firewood and other natural products used as fuel for own final use
242	Fetching water from natural and other sources for own final use
250	Travelling, moving, transporting or accompanying goods or persons related to own-use production of goods
322	Outdoor cleaning
333	Vehicle maintenance and repairs
371	Shopping for/purchasing of goods and related activities
372	Shopping for/availing of services and related activity
380	Travelling, moving, transporting or accompanying goods or persons related to unpaid domestic services for household and family members
441	Travelling related to caregiving services for household and family members
540	Travelling time related to unpaid volunteer, trainee and other unpaid work
640	Travelling time related to learning
750	Travelling time related to socializing and communication, community participation and religious practice
812	Attendance at parks/gardens
813	Attendance at sports events
832	Exercising
860	Travelling time related to culture, leisure, mass media and sports practices
950	Travelling time related to self-care and maintenance activities

Notes: The three-digit codes and descriptions come from the 2016 International Classification of Activities for Time Use Statistics (ICATUS).

Table C2: Alternate Outdoor Activity Classification

	Baseline (1)	Outdoor TUS (2)	Relaxed Classification (3)
Panel A: Both Major and Minor Activity			
$PM2.5\,(\mu g/m^3)$	-0.109***	-0.069*	-0.090**
	(0.036)	(0.037)	(0.037)
Dep. Var. Mean	157.875	333.826	183.107
KP F-Statistic	133.151	133.151	133.151
N	314,125	314,125	314,125
Panel B: Only Major Activity			
$PM2.5\,(\mu g/m^3)$	-0.104***	-0.074**	-0.082**
	(0.036)	(0.037)	(0.036)
Dep. Var. Mean	162.057	334.743	188.395
KP F-Statistic	133.151	133.151	133.151
N	314,125	314,125	314,125

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The dependent variable in all columns is the amount of time spent on outdoor activities in minutes. Activities classified as outdoor are discussed in the main text. The column header shows the activity type. Relaxed classification classify activities as outdoors where the description suggests that most tasks are done outdoors. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables in IV specifications are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C3: Summary Statistics

	N	Mean	SD	Min	Max
Individual Controls					
Sex					
Male	314,125	0.497	0.500	0.00	1.00
Female	314,125	0.503	0.500	0.00	1.00
Marital Status					
Not Currently Married	314,125	0.241	0.428	0.00	1.00
Currently Married	314,125	0.759	0.428	0.00	1.00
Highest Education Level					
Not Literate	314,125	0.236	0.425	0.00	1.00
Up to Primary School	314,125	0.189	0.391	0.00	1.00
Above Primary School	314,125	0.444	0.497	0.00	1.00
College Graduate	314,125	0.131	0.337	0.00	1.00
Usual Principal Activity Status					
Self-Employed	314,125	0.248	0.432	0.00	1.00
Regular Wage/Salaried Employee	314,125	0.136	0.343	0.00	1.00
Casual Labor	314,125	0.165	0.371	0.00	1.00
Unemployed or Not in Labor Force	314,125	0.452	0.498	0.00	1.00

Notes: The sample is restricted to respondents between the ages of 18 and 60. Respondents that do not report their gender as either male or female are dropped. The sample contains data from the India Time Use Survey 2019. Survey weights are used to account for complex survey design.

Table C4: Summary Statistics: Pollution and Weather Conditions

	N	Mean	SD	Min	Max
Pollution					
$PM2.5\,(\mu g/m^3)$	314,125	83.982	73.661	1.76	1602.59
Weather Conditions					
Temperature (K)	314,125	299.196	5.860	243.59	313.81
Precipitation (cm)	314,125	0.017	0.039	0.00	0.75
Wind Speed (m/s)	314,125	1.977	1.286	0.01	11.10

Notes: The sample contains data from the India Time Use Survey 2019. Pollution data is derived from CAMS-EAC4 satellite reanalysis data. Weather Conditions data is derived from ERA5-Land climate reanalysis data.

Table C5: Alternate District Clusters and Wind Direction Bins

	30 Clusters	40 Clusters	50 Clusters	45 Degree Bins	90 Degree Bins	Alternate Instrument
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Both Major and Minor Activity						
$PM2.5\,(\mu g/m^3)$	-0.086**	-0.109***	-0.073**	-0.105***	-0.127***	-0.076**
	(0.037)	(0.036)	(0.031)	(0.038)	(0.043)	(0.038)
Dep. Var. Mean	157.875	157.875	157.875	157.875	157.875	157.875
KP F-Statistic	25.954	133.151	869.359	30.548	17.317	114.107
N	314,125	314,125	314,125	314,125	314,125	314,125
Panel B: Only Major Activity						
$PM2.5\,(\mu g/m^3)$	-0.082**	-0.104***	-0.069**	-0.100***	-0.121***	-0.066*
	(0.038)	(0.036)	(0.032)	(0.039)	(0.043)	(0.039)
Dep. Var. Mean	162.057	162.057	162.057	162.057	162.057	162.057
KP F-Statistic	25.954	133.151	869.359	30.548	17.317	114.107
N	314,125	314,125	314,125	314,125	314,125	314,125

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The dependent variable in all columns is the amount of time spent on outdoor activities. Activities classified as outdoor are discussed in the main text. The column headings indicate the number of clusters that are used to classify districts or the width of the wind direction bin. Alternate instrument in the last column is based on the instrument in Graff Zivin et al. (2023). Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and wind direction bins for the district. Districts are classified into clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C6: Robustness Checks

	Baseline	Normal Day	Drop Outliers	Full Sample	MERRA-2	Add District Time Trends	Add Informant Gender	Weather Non-Linear	Add State-Month Fixed-effects
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Both Major and Minor Activity									
$PM2.5\,(\mu g/m^3)$	-0.109***	-0.102***	-0.083***	-0.080***	-0.143	-0.112**	-0.112***	-0.113***	-0.158***
	(0.036)	(0.037)	(0.029)	(0.029)	(0.103)	(0.045)	(0.035)	(0.038)	(0.056)
Dep. Var. Mean	157.875	161.128	134.601	134.947	157.875	157.875	157.875	157.875	157.875
KP F-Statistic	133.152	120.180	161.012	145.873	82.385	92.197	114.575	68.563	47.287
N	314,125	290,331	299,140	442,607	314,125	314,125	314,125	314,125	314,125
Panel B: Only Major Activity									
$PM2.5\,(\mu g/m^3)$	-0.104***	-0.094**	-0.079**	-0.077***	-0.122	-0.109**	-0.105***	-0.111***	-0.156***
	(0.036)	(0.037)	(0.032)	(0.029)	(0.107)	(0.046)	(0.036)	(0.038)	(0.057)
Dep. Var. Mean	162.057	165.262	143.439	138.449	162.057	162.057	162.057	162.057	162.057
KP F-Statistic	133.152	120.180	144.737	145.873	82.385	92.197	114.575	68.563	47.287
N	314,125	290,331	302,630	442,607	314,125	314,125	314,125	314,125	314,125

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female, except for column (4). The dependent variable in all columns is the amount of time spent on outdoor activities in minutes. Activities classified as outdoor are discussed in the main text. In column (2), the sample is restricted to days classified as "normal" according to the survey. In column (3), the sample is restricted to respondents who report time spent on outdoor activities below the 95th percentile of the sample. Column (4) includes all respondents who are above the age of six, irrespective of their reported gender. In column (5), CAMS-EAC4 $PM2.5$ concentration measure is replaced with MERRA-2 $PM2.5$ concentration measure. In column (6), district-month linear trends are included. In column (7), the gender of the respondent is controlled for. In column (8), weather controls enter non-linearly in the specification with an indicator for each quintile of the weather condition distribution. In column (9), state-survey month fixed-effects are included. Each specification in relevant columns includes eather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C7: Effect of Air Pollution on Number of Interviews

	IV (1)
$PM2.5\,(\mu g/m^3)$	-0.00102
	(0.00109)
Weather Controls	✓
District FE	✓
Calendar Date FE	✓
Dep. Var. Mean	2.914
KP F-Statistic	71.190
N	47,298

Notes: Heteroskedasticity robust standard errors clustered by district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique district and date. The dependent variable in each column is the number of interviews conducted. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C8: Other Pollutants

	Baseline (1)	Ozone (2)	NO2 (3)	SO2 (4)	NO (5)	CO (6)
Panel A: Both Major and Minor Activity						
$PM2.5\,(\mu g/m^3)$	-0.109***	-0.113***	-0.101***	-0.096**	-0.059	-0.090**
	(0.036)	(0.037)	(0.036)	(0.044)	(0.054)	(0.041)
$O_3\,(\mu g/m^2)$		-0.000				
		(0.000)				
$NO_2\,(\mu g/m^2)$			-0.003			
			(0.002)			
$SO_2\,(\mu g/m^2)$				-0.000		
				(0.001)		
$NO\,(\mu g/m^2)$					-0.013	
					(0.009)	
$CO\,(\mu g/m^2)$						-0.000
						(0.000)
Dep. Var. Mean	157.875	157.875	157.875	157.875	157.875	157.875
KP F-Statistic	133.152	42.717	53.920	59.024	46.573	86.160
N	314,125	314,125	314,125	314,125	314,125	314,125
Panel B: Only Major Activity						
$PM2.5\,(\mu g/m^3)$	-0.104***	-0.108***	-0.094**	-0.091**	-0.038	-0.079*
	(0.036)	(0.037)	(0.037)	(0.045)	(0.055)	(0.042)
$O_3\,(\mu g/m^2)$		-0.000				
		(0.000)				
$NO_2\,(\mu g/m^2)$			-0.003			
			(0.002)			
$SO_2\,(\mu g/m^2)$				-0.000		
				(0.001)		
$NO\,(\mu g/m^2)$					-0.018*	
					(0.010)	
$CO\,(\mu g/m^2)$						-0.000
						(0.000)
Dep. Var. Mean	162.057	162.057	162.057	162.057	162.057	162.057
KP F-Statistic	133.152	42.717	53.920	59.024	46.573	86.160
N	314,125	314,125	314,125	314,125	314,125	314,125

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The dependent variable in all columns is the amount of time spent on outdoor activities. Activities classified as outdoor are discussed in the main text. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C9: Particulate Matter of Other Size

	Baseline (1)	PM1 (2)	PM10 (3)
Panel A: Both Major and Minor Activity			
$PM2.5\,(\mu g/m^3)$	-0.109***		
	(0.036)		
$PM1\,(\mu g/m^3)$		-0.133***	
		(0.042)	
$PM10\,(\mu g/m^3)$			-0.075***
			(0.025)
Dep. Var. Mean	157.875	157.875	157.875
KP F-Statistic	133.151	112.806	130.791
N	314,125	314,125	314,125
Panel B: Only Major Activity			
$PM2.5\,(\mu g/m^3)$	-0.104***		
	(0.036)		
$PM1\,(\mu g/m^3)$		-0.125***	
		(0.043)	
$PM10\,(\mu g/m^3)$			-0.071***
			(0.026)
Dep. Var. Mean	162.057	162.057	162.057
KP F-Statistic	133.151	112.806	130.791
N	314,125	314,125	314,125

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The dependent variable in all columns is the amount of time spent on outdoor activities. Activities classified as outdoor are discussed in the main text. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C10: Including Lags or Leads of Air Pollution

	Baseline Baseline Instruments (1)	Include Lag and Lead Baseline Instruments (2)	Include Lag and Lead Graff Zivin et al. (2023) Instruments (3)
Panel A: Both Major and Minor Activity			
$PM2.5\,(\mu g/m^3)$	-0.109***	-0.134	-0.145
	(0.036)	(0.119)	(0.110)
$PM2.5\,(\mu g/m^3)$ Lead		-0.039	0.028
		(0.111)	(0.115)
$PM2.5\,(\mu g/m^3)$ Lag		0.052	0.037
		(0.086)	(0.098)
Dep. Var. Mean	157.875	157.875	157.875
KP F-Statistic	133.151	28.468	17.282
N	314,125	314,125	314,125
Panel B: Only Major Activity			
$PM2.5\,(\mu g/m^3)$	-0.104***	-0.122	-0.139
	(0.036)	(0.122)	(0.111)
$PM2.5\,(\mu g/m^3)$ Lead		-0.052	0.036
		(0.114)	(0.118)
$PM2.5\,(\mu g/m^3)$ Lag		0.058	0.035
		(0.088)	(0.098)
Dep. Var. Mean	162.057	162.057	162.057
KP F-Statistic	133.151	28.468	17.282
N	314,125	314,125	314,125

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The dependent variable in all columns is the amount of time spent on outdoor activities. Activities classified as outdoor are discussed in the main text. Instrumental variables in the last column are based on the framework in Graff Zivin et al. (2023). Instrumental variables in other columns are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C11: Heterogeneity by Major Activity Classification – Full Table with no age restrictions

	Indoor				Outdoor			
	Employment	Production For Own Use	Unpaid Care	Leisure	Employment	Production For Own Use	Unpaid Care	Leisure
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Both Major and Minor Activity								
$PM2.5\,(\mu g/m^3)$	-0.001	0.002	0.046**	0.033	-0.082***	0.001	0.017***	-0.015**
	(0.025)	(0.003)	(0.020)	(0.033)	(0.026)	(0.016)	(0.005)	(0.006)
Dep. Var. Mean	86.505	1.340	144.376	1072.826	77.208	23.900	13.781	20.065
KP F-Statistic	145.960	145.960	145.960	145.960	145.960	145.960	145.960	145.960
N	442,480	442,480	442,480	442,480	442,480	442,480	442,480	442,480
Panel B: Only Major Activity								
$PM2.5\,(\mu g/m^3)$	0.008	0.002	0.046**	0.020	-0.078***	0.002	0.016***	-0.017**
	(0.026)	(0.003)	(0.020)	(0.033)	(0.026)	(0.016)	(0.006)	(0.007)
Dep. Var. Mean	91.228	1.454	152.513	1056.349	79.946	24.827	12.992	20.690
KP F-Statistic	145.960	145.960	145.960	145.960	145.960	145.960	145.960	145.960
N	442,480	442,480	442,480	442,480	442,480	442,480	442,480	442,480

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to those who report their gender to be either male or female. The dependent variable in all columns is the amount of time spent on outdoor activities in minutes in the major division. Activities classified as outdoor are discussed in the main text. Nine major activity divisions based on the first digit of the 3-digit activity code from ICATUS 2016 are further classified into four major divisions. The column headings indicate which major divisions are grouped together. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C12: Extensive and Intensive Margin of Employment Related Outdoor Activities

	Intensive Margin (1)	Extensive Margin (2)
Panel A: Both Major and Minor Activity		
$PM2.5\,(\mu g/m^3)$	-0.1063***	-0.0001
	(0.0325)	(0.0001)
Dep. Var. Mean	99.663	0.416
KP F-Statistic	133.151	133.151
N	314,125	314,125
Panel B: Only Major Activity		
$PM2.5\,(\mu g/m^3)$	-0.1001***	-0.0001
	(0.0330)	(0.0001)
Dep. Var. Mean	103.226	0.412
KP F-Statistic	133.151	133.151
N	314,125	314,125

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The dependent variable in the first column is the amount of time spent on outdoor employment related activities in minutes. The dependent variable in the last column is an indicator of whether any time is spent on outdoor employment related activities. Activities classified as outdoor are discussed in the main text. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C13: Heterogeneity by Employer Status

	Employer (1)	Non-employer (2)
Panel A: Both Major and Minor Activity		
$PM2.5\,(\mu g/m^3)$	-0.155**	-0.175***
	(0.072)	(0.064)
Dep. Var. Mean	257.021	222.339
KP F-Statistic	69.087	114.195
N	64,168	107,941
Panel B: Only Major Activity		
$PM2.5\,(\mu g/m^3)$	-0.130*	-0.172***
	(0.071)	(0.065)
Dep. Var. Mean	266.059	229.755
KP F-Statistic	69.087	114.195
N	64,168	107,941

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. Additionally, the sample is restricted to those respondents who report their usual principal activity status as either self-employed, casual labor, or regular salaried employee. The dependent variable in all columns is the amount of time spent on outdoor activities in minutes. Activities classified as outdoor are discussed in the main text. The column headings indicate the subpopulation. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C14: Effect of Air Pollution on Time Spent Outdoors – Employment Related Activities

	Employment related activities	Code 12 Employment in household enterprises to produce goods	Code 121 Growing of crops for the market	Code 128 Construction activities for the market
	(1)	(2)	(3)	(4)
Panel A: Both Major and Minor Activity				
$PM2.5\,(\mu g/m^3)$	-0.106***	-0.074***	-0.060**	-0.016
	(0.032)	(0.026)	(0.024)	(0.015)
Dep. Var. Mean	99.663	62.524	39.862	17.307
KP F-Statistic	133.151	120.791	120.791	120.791
N	314,125	314,125	314,125	314,125
Panel B: Only Major Activity				
$PM2.5\,(\mu g/m^3)$	-0.100***	-0.072***	-0.059**	-0.015
	(0.033)	(0.026)	(0.024)	(0.015)
Dep. Var. Mean	103.226	65.103	41.465	18.012
KP F-Statistic	133.151	120.791	120.791	120.791
N	314,125	314,125	314,125	314,125

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The dependent variable in all columns is the amount of time spent on outdoor activities in the respective activity code. Activities classified as outdoor are discussed in the main text. The column headings indicate which activity codes are used for time-use computation. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C15: Effect of Air Pollution on Time Spent Outdoors – Unpaid Care Related Activities

	Unpaid care related activities	Code 3 Unpaid domestic services for household and family members	Code 4 Unpaid caregiving services for household and family members	Code 5 Unpaid volunteer, trainee and other unpaid and other work	Code 37 Shopping for own household and family members	Code 38 Travelling, moving or accompanying goods or persons
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Both Major and Minor Activity						
$PM2.5\,(\mu g/m^3)$	0.017***	0.014**	0.001	0.003	0.006	0.006***
	(0.006)	(0.005)	(0.001)	(0.002)	(0.004)	(0.002)
Dep. Var. Mean	16.586	15.244	0.314	1.028	5.630	1.944
KP F-Statistic	133.151	133.151	133.151	133.151	133.151	133.151
N	314,125	314,125	314,125	314,125	314,125	314,125
Panel B: Only Major Activity						
$PM2.5\,(\mu g/m^3)$	0.016**	0.012**	0.001	0.003	0.006	0.004**
	(0.006)	(0.006)	(0.001)	(0.003)	(0.004)	(0.002)
Dep. Var. Mean	15.559	14.213	0.328	1.018	6.044	1.866
KP F-Statistic	133.151	133.151	133.151	133.151	133.151	133.151
N	314,125	314,125	314,125	314,125	314,125	314,125

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The dependent variable in all columns is the amount of time spent on outdoor activities in the respective activity code. Activities classified as outdoor are discussed in the main text. The column headings indicate which activity codes are used for time-use computation. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C16: Effect of Air Pollution on Time Spent Indoors – Leisure

	Leisure	Code 6 Learning	Code 7 Socializing and communication, community participation and religious practice	Code 8 Culture, leisure mass media and sports practices	Code 9 Self-care and maintenance	Code 71 Socializing and communication	Code 711 Talking, conversing, chatting activities	Code 712 Socializing, getting together and gathering	Code 84 Mass media use	Code 85 Activities associated with reflecting, resting, relaxing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Both Major and Minor Activity										
$PM2.5\,(\mu g/m^3)$	0.076**	-0.025	0.047	0.065***	-0.010	0.050*	0.020	0.022*	0.058***	0.012
	(0.037)	(0.015)	(0.029)	(0.022)	(0.028)	(0.028)	(0.024)	(0.013)	(0.016)	(0.018)
Dep. Var. Mean	983.786	27.449	128.978	123.607	703.753	112.484	92.029	17.709	74.435	43.391
KP F-Statistic	133.151	133.151	133.151	133.151	133.151	133.151	133.151	133.151	133.151	133.151
N	314,125	314,125	314,125	314,125	314,125	314,125	314,125	314,125	314,125	314,125
Panel B: Only Major Activity										
$PM2.5\,(\mu g/m^3)$	0.058	-0.026*	0.007	0.056**	0.021	0.007	-0.015	0.017	0.048***	0.012
	(0.036)	(0.015)	(0.021)	(0.023)	(0.030)	(0.020)	(0.018)	(0.012)	(0.017)	(0.019)
Dep. Var. Mean	962.962	28.171	91.373	123.432	719.985	74.750	55.349	16.936	73.480	43.982
KP F-Statistic	133.151	133.151	133.151	133.151	133.151	133.151	133.151	133.151	133.151	133.151
N	314,125	314,125	314,125	314,125	314,125	314,125	314,125	314,125	314,125	314,125

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The dependent variable in all columns is the amount of time spent on indoor activities in the respective activity code. Activities classified as indoor are discussed in the main text. The column headings indicate which activity codes are used for time-use computation. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C17: Heterogeneity by Age – Full Table

	Age $\leq$ 22 (1)	23 $\leq$ Age $\leq$ 45 (2)	46 $\leq$ Age $\leq$ 60 (3)	Age $>$ 60 (4)
Panel A: Both Major and Minor Activity				
$PM2.5\,(\mu g/m^3)$	-0.028	-0.112***	-0.124**	0.013
	(0.025)	(0.038)	(0.053)	(0.043)
Dep. Var. Mean	76.818	161.104	177.763	119.587
KP F-Statistic	70.478	116.748	74.315	104.925
N	131,893	192,952	76,137	41,498
Panel B: Only Major Activity				
$PM2.5\,(\mu g/m^3)$	-0.028	-0.108***	-0.115**	0.006
	(0.025)	(0.039)	(0.054)	(0.045)
Dep. Var. Mean	78.487	165.236	182.800	123.169
KP F-Statistic	70.478	116.748	74.315	104.925
N	131,893	192,952	76,137	41,498

Notes: Heteroskedasticity robust standard errors clustered by district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The dependent variable in all columns is the amount of time spent on outdoor activities. Activities classified as outdoor are discussed in the main text. Age restrictions for the sample are mentioned in the column header. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C18: Heterogeneity by Usual Principal Activity Status – Full Table

	Self-Employed	Regular Wage/ Salaried Employee	Casual Labor	Unemployed or Not in Labor Force
	(1)	(2)	(3)	(4)
Panel A: Both Major and Minor Activity				
$PM2.5\,(\mu g/m^3)$	-0.168**	-0.043	-0.291***	-0.007
	(0.070)	(0.036)	(0.103)	(0.021)
Dep. Var. Mean	256.753	127.099	305.426	64.081
KP F-Statistic	57.745	94.973	72.214	88.065
N	79,556	45,996	46,557	142,016
Panel B: Only Major Activity				
$PM2.5\,(\mu g/m^3)$	-0.151**	-0.041	-0.285***	-0.003
	(0.069)	(0.040)	(0.099)	(0.022)
Dep. Var. Mean	265.540	131.204	316.006	63.610
KP F-Statistic	57.745	94.973	72.214	88.065
N	79,556	45,996	46,557	142,016

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The dependent variable in all columns is the amount of time spent on outdoor activities in minutes. Activities classified as outdoor are discussed in the main text. The column headings indicate the subpopulation. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C19: Heterogeneity by Usual Principal Activity Status – Drop Days with $PM2.5\,(\mu g/m^3) > 250$

	Self-Employed	Regular Wage/ Salaried Employee	Casual Labor	Unemployed or Not in Labor Force
	(1)	(2)	(3)	(4)
Panel A: Both Major and Minor Activity				
$PM2.5\,(\mu g/m^3)$	-0.168*	0.021	-0.247*	0.033
	(0.098)	(0.076)	(0.142)	(0.035)
Dep. Var. Mean	257.926	127.279	305.367	64.665
KP F-Statistic	90.826	96.818	69.478	124.436
N	76,771	44,219	45,070	135,749
Panel B: Only Major Activity				
$PM2.5\,(\mu g/m^3)$	-0.121	0.028	-0.245*	0.047
	(0.100)	(0.078)	(0.136)	(0.036)
Dep. Var. Mean	266.844	131.489	316.060	64.265
KP F-Statistic	90.826	96.818	69.478	124.436
N	76,771	44,219	45,070	135,749

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. Further, all days where the $PM2.5$ concentration is above $250\mu g/m^3$ are dropped from the estimation sample. The dependent variable in all columns is the amount of time spent on outdoor activities in minutes. Activities classified as outdoor are discussed in the main text. The column headings indicate the subpopulation. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C20: Pollution Episode Estimates

	Preceding Day High Pollution	Two Preceding Days High Pollution	Three Preceding Days High Pollution	Four Preceding Days High Pollution	Five Preceding Days High Pollution
Panel A: Both Major and Minor Activity					
$PM2.5\,(\mu g/m^3)$	-0.065*	-0.051	-0.034	-0.014	0.025
	(0.037)	(0.038)	(0.041)	(0.046)	(0.050)
Dep. Var. Mean	159.892	159.630	159.080	158.232	157.383
KP F-Statistic	46.093	36.083	51.876	80.686	167.067
N	129,395	92,052	69,356	53,343	42,056
Panel B: Only Major Activity					
$PM2.5\,(\mu g/m^3)$	-0.071*	-0.059	-0.041	-0.020	0.016
	(0.037)	(0.038)	(0.041)	(0.047)	(0.052)
Dep. Var. Mean	164.056	163.616	162.954	162.216	161.186
KP F-Statistic	46.093	36.083	51.876	80.686	167.067
N	129,395	92,052	69,356	53,343	42,056

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The dependent variable in all columns is the amount of time spent on outdoor activities in minutes. Activities classified as outdoor are discussed in the main text. The column headings indicate the subpopulation. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C21: Heterogeneity by Industry Risk – Full Table

	Baseline	Low-risk	High-risk
	(1)	(2)	(3)
Panel A: Both Major and Minor Activity			
$PM2.5\,(\mu g/m^3)$	-0.109***	0.002	-0.232***
	(0.036)	(0.030)	(0.069)
Dep. Var. Mean	157.875	103.071	295.623
KP F-Statistic	133.151	107.291	72.411
N	314,125	53,946	118,163
Panel B: Only Major Activity			
$PM2.5\,(\mu g/m^3)$	-0.104***	0.008	-0.217***
	(0.036)	(0.033)	(0.069)
Dep. Var. Mean	162.057	105.850	306.037
KP F-Statistic	133.151	107.291	72.411
N	314,125	53,946	118,163

Notes: Heteroskedasticity robust standard errors clustered by district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. In all the columns, the sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. In columns (2) and (3), the sample is further restricted to those respondents who report being employed as their usual principal activity status. In column (2), the sample is restricted to industries that are classified as low-risk. In column (3), the sample is restricted to industries that are classified as high-risk. This classification is discussed in the main text. The dependent variable in all columns is the amount of time spent on outdoor activities in minutes. Activities classified as outdoor are discussed in the main text. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C22: Heterogeneity by Usual Monthly Consumption Expenditure for Self-Employed and Casual Laborers Only

	< Median MPCE	> Median MPCE
	(1)	(2)
Panel A: Both Major and Minor Activity		
$PM2.5\,(\mu g/m^3)$	-0.118	-0.287***
	(0.087)	(0.083)
Dep. Var. Mean	295.112	254.324
KP F-Statistic	49.276	93.490
N	63,067	63,046
Panel B: Only Major Activity		
$PM2.5\,(\mu g/m^3)$	-0.112	-0.264***
	(0.087)	(0.081)
Dep. Var. Mean	305.187	263.147
KP F-Statistic	49.276	93.490
N	63,067	63,046

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. Additionally, the sample is restricted to those respondents who report their usual principal activity status as either self-employed or casual labor. The dependent variable in all columns is the amount of time spent on outdoor activities in minutes. Activities classified as outdoor are discussed in the main text. The column headings indicate the subpopulation. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C23: Heterogeneity by Education Level – Full Table

	Illiterate (1)	Up to Primary School (2)	Above Primary School (3)	College (4)
Panel A: Both Major and Minor Activity				
$PM2.5\,(\mu g/m^3)$	-0.190***	-0.171**	-0.058	0.019
	(0.064)	(0.067)	(0.042)	(0.027)
Dep. Var. Mean	193.294	191.915	161.929	101.583
KP F-Statistic	59.625	72.239	91.272	88.063
N	63,654	52,363	111,307	41,765
Panel B: Only Major Activity				
$PM2.5\,(\mu g/m^3)$	-0.187***	-0.152**	-0.055	0.009
	(0.064)	(0.069)	(0.042)	(0.029)
Dep. Var. Mean	197.504	197.252	166.492	104.584
KP F-Statistic	59.625	72.239	91.272	88.063
N	63,654	52,363	111,307	41,765

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 23 and 60 and those who report their gender to be either male or female. The dependent variable in all columns is the amount of time spent on outdoor activities in minutes. Activities classified as outdoor are discussed in the main text. The column headings indicate the subpopulation. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C24: Heterogeneity by Gender, Location, Consumption Expenditures, and Dwelling Type – Full Table

	Male	Female	Rural	Urban	< Median MPCE	> Median MPCE	Concrete Dwelling	Non-concrete Dwelling
Panel A: Both Major and Minor Activity								
$PM2.5\,(\mu g/m^3)$	-0.144***	-0.075**	-0.127**	-0.021	-0.073	-0.123***	-0.075**	-0.143**
	(0.052)	(0.030)	(0.053)	(0.024)	(0.053)	(0.032)	(0.034)	(0.058)
Dep. Var. Mean	224.675	91.689	196.254	100.213	180.088	135.661	137.792	193.574
KP F-Statistic	119.191	119.898	43.151	143.233	42.765	132.944	139.980	54.312
N	156,338	157,787	188,598	125,527	157,064	157,057	201,029	113,096
Panel B: Only Major Activity								
$PM2.5\,(\mu g/m^3)$	-0.142***	-0.065**	-0.119**	-0.019	-0.070	-0.117***	-0.074**	-0.127**
	(0.053)	(0.031)	(0.054)	(0.025)	(0.053)	(0.033)	(0.035)	(0.059)
Dep. Var. Mean	232.918	91.846	201.792	102.357	184.821	139.292	141.647	198.335
KP F-Statistic	119.191	119.898	43.151	143.233	42.765	132.944	139.980	54.312
N	156,338	157,787	188,598	125,527	157,064	157,057	201,029	113,096

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The dependent variable in all columns is the amount of time spent on outdoor activities in minutes. Activities classified as outdoor are discussed in the main text. The column headings indicate the subpopulation. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C25: Heterogeneity by Whether Household has Dependents

	Baseline	Have No Dependents	Have Some Dependents
	(1)	(2)	(3)
Panel A: Both Major and Minor Activity			
$PM2.5\,(\mu g/m^3)$	-0.109***	-0.123***	-0.094**
	(0.036)	(0.041)	(0.042)
Dep. Var. Mean	157.875	157.884	157.863
KP F-Statistic	133.151	121.994	71.555
N	314,125	187,586	126,539
Panel B: Only Major Activity			
$PM2.5\,(\mu g/m^3)$	-0.104***	-0.118***	-0.085**
	(0.036)	(0.041)	(0.043)
Dep. Var. Mean	162.057	161.959	162.202
KP F-Statistic	133.151	121.994	71.555
N	314,125	187,586	126,539

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The households with at least one member who is below the age of six or above the age of 60 are desginated to have dependents. The dependent variable in all columns is the amount of time spent on outdoor activities in minutes. Activities classified as outdoor are discussed in the main text. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C26: Male Share in Major Activity Classification

	Indoor				Outdoor			
	Employment	Production For Own Use	Unpaid Care	Leisure	Employment	Production For Own Use	Unpaid Care	Leisure
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Both Major and Minor Activity								
$PM2.5\,(\mu g/m^3)$	0.007	-0.002	0.001	0.003	-0.008	-0.007	0.019*	-0.018
	(0.013)	(0.002)	(0.003)	(0.002)	(0.010)	(0.008)	(0.010)	(0.012)
Dep. Var. Mean	48.825	0.857	6.820	51.076	68.164	14.387	18.103	22.997
KP F-Statistic	122.742	122.742	122.742	122.742	122.742	122.742	122.742	122.742
N	106,579	106,579	106,579	106,579	106,579	106,579	106,579	106,579
Panel B: Only Major Activity								
$PM2.5\,(\mu g/m^3)$	0.010	-0.002	0.001	0.003	-0.005	-0.009	0.013	-0.020*
	(0.013)	(0.002)	(0.003)	(0.002)	(0.011)	(0.008)	(0.010)	(0.012)
Dep. Var. Mean	48.504	0.764	6.611	51.158	67.647	14.166	17.811	21.992
KP F-Statistic	122.742	122.742	122.742	122.742	122.742	122.742	122.742	122.742
N	106,579	106,579	106,579	106,579	106,579	106,579	106,579	106,579

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The sample includes households that have at least one male and female member. The dependent variable in all columns is the ratio of time spent on outdoor activities in minutes in the respective activity code by male to all members of the households. Activities classified as outdoor are discussed in the main text. Nine activity divisions based on the first digit of the 3-digit activity code from ICATUS 2016 are further classified into four major divisions. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C27: Heterogeneity by Major Activity Classification – Male Respondents Only

	Indoor				Outdoor			
	Employment	Production For Own Use	Unpaid Care	Leisure	Employment	Production For Own Use	Unpaid Care	Leisure
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Both Major and Minor Activity								
$PM2.5\,(\mu g/m^3)$	0.001	0.002	0.016	0.126***	-0.134***	-0.020	0.023***	-0.014*
	(0.057)	(0.006)	(0.015)	(0.043)	(0.051)	(0.024)	(0.009)	(0.008)
Dep. Var. Mean	189.724	1.416	32.687	991.498	162.601	30.783	13.648	17.643
KP F-Statistic	119.191	119.191	119.191	119.191	119.191	119.191	119.191	119.191
N	156,338	156,338	156,338	156,338	156,338	156,338	156,338	156,338
Panel B: Only Major Activity								
$PM2.5\,(\mu g/m^3)$	0.017	0.001	0.021	0.102**	-0.125**	-0.017	0.019**	-0.019**
	(0.060)	(0.006)	(0.015)	(0.042)	(0.052)	(0.024)	(0.009)	(0.009)
Dep. Var. Mean	200.177	1.500	33.811	971.594	168.354	32.049	14.127	18.388
KP F-Statistic	119.191	119.191	119.191	119.191	119.191	119.191	119.191	119.191
N	156,338	156,338	156,338	156,338	156,338	156,338	156,338	156,338

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be male. The dependent variable in all columns is the amount of time spent on activities in minutes in the major division. Activities classified as outdoor are discussed in the main text. Nine activity divisions based on the first digit of the 3-digit activity code from ICATUS 2016 are further classified into four major divisions. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C28: Heterogeneity by Major Activity Classification – Female Respondents Only

	Indoor				Outdoor			
	Employment	Production For Own Use	Unpaid Care	Leisure	Employment	Production For Own Use	Unpaid Care	Leisure
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Both Major and Minor Activity								
$PM2.5\,(\mu g/m^3)$	-0.014	0.003	0.058	0.028	-0.082***	-0.002	0.012	-0.003
	(0.019)	(0.004)	(0.041)	(0.044)	(0.024)	(0.018)	(0.008)	(0.006)
Dep. Var. Mean	40.930	1.830	329.406	976.146	37.304	25.786	19.496	9.103
KP F-Statistic	119.898	119.898	119.898	119.898	119.898	119.898	119.898	119.898
N	157,787	157,787	157,787	157,787	157,787	157,787	157,787	157,787
Panel B: Only Major Activity								
$PM2.5\,(\mu g/m^3)$	-0.011	0.005	0.057	0.015	-0.077***	-0.002	0.014*	-0.000
	(0.020)	(0.005)	(0.041)	(0.045)	(0.025)	(0.019)	(0.008)	(0.006)
Dep. Var. Mean	43.047	2.027	348.670	954.409	38.695	26.747	16.978	9.426
KP F-Statistic	119.898	119.898	119.898	119.898	119.898	119.898	119.898	119.898
N	157,787	157,787	157,787	157,787	157,787	157,787	157,787	157,787

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be female. The dependent variable in all columns is the amount of time spent on activities in minutes in the major division. Activities classified as outdoor are discussed in the main text. Nine activity divisions based on the first digit of the 3-digit activity code from ICATUS 2016 are further classified into four major divisions. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C29: Male Share in Major Activity Classification - Only Married Households

	Indoor				Outdoor			
	Employment	Production For Own Use	Unpaid Care	Leisure	Employment	Production For Own Use	Unpaid Care	Leisure
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Both Major and Minor Activity								
$PM2.5\,(\mu g/m^3)$	0.015	-0.002	0.000	0.001	-0.014	-0.006	0.019*	-0.019
	(0.013)	(0.002)	(0.003)	(0.001)	(0.011)	(0.009)	(0.010)	(0.013)
Dep. Var. Mean	45.474	0.793	6.551	50.197	67.149	14.235	16.831	16.633
KP F-Statistic	103.326	103.326	103.326	103.326	103.326	103.326	103.326	103.326
N	87,101	87,101	87,101	87,101	87,101	87,101	87,101	87,101
Panel B: Only Major Activity								
$PM2.5\,(\mu g/m^3)$	0.018	-0.002	0.000	0.001	-0.011	-0.008	0.013	-0.022*
	(0.013)	(0.002)	(0.003)	(0.001)	(0.011)	(0.009)	(0.010)	(0.013)
Dep. Var. Mean	45.122	0.690	6.323	50.286	66.555	14.002	16.497	15.589
KP F-Statistic	103.326	103.326	103.326	103.326	103.326	103.326	103.326	103.326
N	87,101	87,101	87,101	87,101	87,101	87,101	87,101	87,101

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The sample includes households that have at least one male and female member. The dependent variable in all columns is the ratio of time spent on outdoor activities in minutes in the respective activity code by male to all members of the households. Activities classified as outdoor are discussed in the main text. Nine activity divisions based on the first digit of the 3-digit activity code from ICATUS 2016 are further classified into four major divisions. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C30: Heterogeneity by the Number of Households Members

	Baseline	Multi member HH	Single member HH
	(1)	(2)	(3)
Panel A: Both Major and Minor Activity			
$PM2.5\,(\mu g/m^3)$	-0.109***	-0.109***	-0.190**
	(0.036)	(0.037)	(0.079)
Dep. Var. Mean	157.875	158.560	133.115
KP F-Statistic	133.152	124.697	65.255
N	314,125	305,669	8,456
Panel B: Only Major Activity			
$PM2.5\,(\mu g/m^3)$	-0.104***	-0.103***	-0.194**
	(0.036)	(0.037)	(0.082)
Dep. Var. Mean	162.057	162.782	135.827
KP F-Statistic	133.152	124.697	65.255
N	314,125	305,669	8,456

Notes: Heteroskedasticity robust standard errors clustered by district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The dependent variable in each column is the amount of time spent on outdoor activities in minutes. Activities classified as outdoor are discussed in the main text. In column (2), the sample is restricted to multiple-member households. In column (3), the sample is restricted to single-member households. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the Time Use Survey 2019.

Table C31: Intraday Effect of Air Pollution Concentration on Time Outdoors

	7AM - 1PM (1)	1PM - 7PM (2)	7PM - 7AM (3)
Panel A: Both Major and Minor Activity			
$PM2.5\,(\mu g/m^3)$	-0.038	-0.088***	-0.000
	(0.025)	(0.029)	(0.004)
Dep. Var. Mean	75.002	66.023	16.850
KP F-Statistic	44.261	76.357	83.282
N	314,125	314,125	314,125
Panel B: Only Major Activity			
$PM2.5\,(\mu g/m^3)$	-0.035	-0.091***	-0.000
	(0.025)	(0.030)	(0.004)
Dep. Var. Mean	76.995	68.151	16.911
KP F-Statistic	44.261	76.357	83.282
N	314,125	314,125	314,125

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The dependent variable in all columns is the amount of time spent on outdoor activities. Activities classified as outdoor are discussed in the main text. The column headings indicate which time intervals are grouped together. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C32: Within Day Time-Use Effect of Air Pollution on Time Spent Outdoors – Heterogeneity by Usual Principal Activity Status

	Self-Employed			Regular Wage/Salaried Employee			Casual Labor			Unemployed or Not in Labor Force		
	7AM - 1PM	1PM - 7PM	7PM - 7AM	7AM - 1PM	1PM - 7PM	7PM - 7AM	7AM - 1PM	1PM - 7PM	7PM - 7AM	7AM - 1PM	1PM - 7PM	7PM - 7AM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Both Major and Minor Activity												
$PM2.5\,(\mu g/m^3)$	-0.065	-0.126**	-0.004	-0.038	-0.021	-0.001	-0.079	-0.326***	0.008	0.005	-0.001	0.001
	(0.050)	(0.057)	(0.008)	(0.028)	(0.034)	(0.007)	(0.073)	(0.080)	(0.013)	(0.015)	(0.018)	(0.004)
Dep. Var. Mean	126.596	105.091	25.066	53.658	48.175	25.266	152.384	133.359	19.683	27.643	27.844	8.594
KP F-Statistic	31.484	36.478	48.528	56.878	48.429	94.310	41.954	37.458	77.553	55.329	58.536	81.205
N	79,556	79,556	79,556	45,996	45,996	45,996	46,557	46,557	46,557	142,016	142,016	142,016
Panel B: Only Major Activity												
$PM2.5\,(\mu g/m^3)$	-0.056	-0.126**	-0.008	-0.046	-0.024	0.000	-0.077	-0.327***	0.002	0.009	-0.000	0.004
	(0.050)	(0.057)	(0.009)	(0.029)	(0.036)	(0.008)	(0.070)	(0.081)	(0.013)	(0.015)	(0.020)	(0.004)
Dep. Var. Mean	131.084	108.763	25.692	55.297	49.675	26.232	157.815	138.188	20.003	27.227	28.423	7.959
KP F-Statistic	31.484	36.478	48.528	56.878	48.429	94.310	41.954	37.458	77.553	55.329	58.536	81.205
N	79,556	79,556	79,556	45,996	45,996	45,996	46,557	46,557	46,557	142,016	142,016	142,016

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The dependent variable in all columns is the amount of time spent on outdoor activities in minutes in the major division. Activities classified as outdoor are discussed in the main text. The column headings indicate the subpopulation. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C33: Intraday Heterogeneity by Major Activity Classification – Full Table

	Indoor											
	Employment			Production For Own Use			Unpaid Care			Leisure		
	7AM - 1PM	1PM - 7PM	7PM - 7AM	7AM - 1PM	1PM - 7PM	7PM - 7AM	7AM - 1PM	1PM - 7PM	7PM - 7AM	7AM - 1PM	1PM - 7PM	7PM - 7AM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Both Major and Minor Activity												
$PM2.5\,(\mu g/m^3)$	-0.008	-0.007	-0.004	0.004	-0.001	0.000	0.012	0.052***	-0.016**	0.029	0.044	0.020**
	(0.021)	(0.027)	(0.004)	(0.002)	(0.003)	(0.000)	(0.013)	(0.018)	(0.007)	(0.024)	(0.029)	(0.010)
Dep. Var. Mean	51.545	54.160	9.280	0.738	0.757	0.129	81.010	48.373	52.347	151.706	190.687	641.393
KP F-Statistic	44.261	76.357	83.282	44.261	76.357	83.282	44.261	76.357	83.282	44.261	76.357	83.282
N	314,125	314,125	314,125	314,125	314,125	314,125	314,125	314,125	314,125	314,125	314,125	314,125
Panel B: Only Major Activity												
$PM2.5\,(\mu g/m^3)$	0.005	-0.015	-0.003	0.005*	-0.001	0.000	0.013	0.052***	-0.020***	0.012	0.054**	0.023**
	(0.021)	(0.028)	(0.005)	(0.003)	(0.003)	(0.000)	(0.013)	(0.019)	(0.007)	(0.021)	(0.027)	(0.010)
Dep. Var. Mean	54.335	57.149	9.766	0.799	0.822	0.143	85.090	51.088	55.788	142.780	182.790	637.391
KP F-Statistic	44.261	76.357	83.282	44.261	76.357	83.282	44.261	76.357	83.282	44.261	76.357	83.282
N	314,125	314,125	314,125	314,125	314,125	314,125	314,125	314,125	314,125	314,125	314,125	314,125
	Outdoor											
Panel C: Both Major and Minor Activity												
$PM2.5\,(\mu g/m^3)$	-0.051**	-0.101***	0.001	0.009	0.001	-0.001	0.005	0.014**	0.002	0.000	-0.001	-0.002
	(0.023)	(0.026)	(0.003)	(0.012)	(0.014)	(0.002)	(0.004)	(0.007)	(0.002)	(0.003)	(0.004)	(0.002)
Dep. Var. Mean	50.569	42.228	6.866	13.738	11.782	2.754	6.018	6.971	3.597	4.678	5.042	3.634
KP F-Statistic	44.261	76.357	83.282	44.261	76.357	83.282	44.261	76.357	83.282	44.261	76.357	83.282
N	314,125	314,125	314,125	314,125	314,125	314,125	314,125	314,125	314,125	314,125	314,125	314,125
Panel D: Only Major Activity												
$PM2.5\,(\mu g/m^3)$	-0.049**	-0.105***	0.002	0.009	0.003	-0.002	0.005	0.012*	0.002	0.000	-0.001	-0.002
	(0.024)	(0.027)	(0.003)	(0.013)	(0.015)	(0.002)	(0.004)	(0.007)	(0.002)	(0.003)	(0.005)	(0.002)
Dep. Var. Mean	52.334	43.751	7.140	14.273	12.292	2.821	5.561	6.817	3.181	4.827	5.291	3.769
KP F-Statistic	44.261	76.357	83.282	44.261	76.357	83.282	44.261	76.357	83.282	44.261	76.357	83.282
N	314,125	314,125	314,125	314,125	314,125	314,125	314,125	314,125	314,125	314,125	314,125	314,125

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The dependent variable in all columns is the amount of time spent on outdoor activities in minutes in the major division. Activities classified as outdoor are discussed in the main text. Nine activity divisions based on the first digit of the 3-digit activity code from ICATUS 2016 are further classified into four major divisions. The column headings indicate which one-digit activity codes are grouped together. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C34: Intraday Heterogeneity by Gender, Location, Consumption Expenditures, and Dwelling Type

	Male			Female			Rural			Urban		
	7AM - 1PM	1PM - 7PM	7PM - 7AM	7AM - 1PM	1PM - 7PM	7PM - 7AM	7AM - 1PM	1PM - 7PM	7PM - 7AM	7AM - 1PM	1PM - 7PM	7PM - 7AM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Both Major and Minor Activity												
$PM2.5\,(\mu g/m^3)$	-0.049	-0.121***	-0.004	-0.035	-0.064**	0.003	-0.042	-0.126***	-0.001	-0.015	-0.017	0.005
	(0.036)	(0.041)	(0.006)	(0.022)	(0.026)	(0.004)	(0.034)	(0.046)	(0.006)	(0.017)	(0.020)	(0.004)
Dep. Var. Mean	108.923	91.901	23.851	41.392	40.383	9.914	96.411	83.343	16.500	42.834	40.001	17.378
KP F-Statistic	31.751	61.007	73.867	57.023	79.056	95.432	47.825	32.900	53.412	90.515	82.223	123.968
N	156,338	156,338	156,338	157,787	157,787	157,787	188,598	188,598	188,598	125,527	125,527	125,527
Panel B: Only Major Activity												
$PM2.5\,(\mu g/m^3)$	-0.048	-0.129***	-0.007	-0.030	-0.061**	0.006	-0.034	-0.127***	-0.003	-0.016	-0.019	0.004
	(0.037)	(0.042)	(0.007)	(0.023)	(0.027)	(0.004)	(0.034)	(0.047)	(0.007)	(0.018)	(0.021)	(0.005)
Dep. Var. Mean	112.932	95.253	24.733	41.388	41.297	9.161	99.305	86.156	16.332	43.476	41.099	17.782
KP F-Statistic	31.751	61.007	73.867	57.023	79.056	95.432	47.825	32.900	53.412	90.515	82.223	123.968
N	156,338	156,338	156,338	157,787	157,787	157,787	188,598	188,598	188,598	125,527	125,527	125,527
	< Median MPCE			> Median MPCE			Concrete Dwelling			Non-concrete Dwelling		
Panel A: Both Major and Minor Activity												
$PM2.5\,(\mu g/m^3)$	-0.012	-0.088**	0.003	-0.061***	-0.082***	0.001	-0.037	-0.074***	0.002	-0.057	-0.144***	-0.003
	(0.035)	(0.045)	(0.006)	(0.023)	(0.024)	(0.004)	(0.024)	(0.028)	(0.004)	(0.040)	(0.050)	(0.007)
Dep. Var. Mean	88.008	76.757	15.324	61.994	55.289	18.377	63.793	56.551	17.447	94.924	82.860	15.790
KP F-Statistic	39.835	35.813	57.820	71.857	61.816	109.417	55.296	64.160	93.505	43.034	53.747	93.390
N	157,064	157,064	157,064	157,057	157,057	157,057	201,029	201,029	201,029	113,096	113,096	113,096
Panel B: Only Major Activity												
$PM2.5\,(\mu g/m^3)$	-0.011	-0.093**	0.003	-0.059**	-0.082***	0.000	-0.032	-0.081***	0.003	-0.058	-0.137***	-0.005
	(0.035)	(0.045)	(0.006)	(0.025)	(0.024)	(0.005)	(0.025)	(0.029)	(0.005)	(0.041)	(0.052)	(0.007)
Dep. Var. Mean	90.452	79.233	15.135	63.537	57.068	18.687	65.437	58.526	17.684	97.540	85.258	15.537
KP F-Statistic	39.835	35.813	57.820	71.857	61.816	109.417	55.296	64.160	93.505	43.034	53.747	93.390
N	157,064	157,064	157,064	157,057	157,057	157,057	201,029	201,029	201,029	113,096	113,096	113,096

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The dependent variable in all columns is the amount of time spent on outdoor activities. Activities classified as outdoor are discussed in the main text. The column headings indicate the subpopulation. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C35: Intraday Heterogeneity by Age

	Age ≤ 22			23 ≤ Age ≤ 45			46 ≤ Age ≤ 60			Age > 60		
	7AM - 1PM	1PM - 7PM	7PM - 7AM	7AM - 1PM	1PM - 7PM	7PM - 7AM	7AM - 1PM	1PM - 7PM	7PM - 7AM	7AM - 1PM	1PM - 7PM	7PM - 7AM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Both Major and Minor Activity												
$PM2.5\,(\mu g/m^3)$	0.004	0.005	0.002	-0.040	-0.092***	-0.001	-0.051	-0.135***	-0.002	0.025	0.001	0.003
	(0.017)	(0.020)	(0.004)	(0.026)	(0.031)	(0.004)	(0.038)	(0.038)	(0.006)	(0.035)	(0.038)	(0.007)
Dep. Var. Mean	36.612	33.974	6.232	76.275	67.705	17.124	85.429	72.398	19.936	57.794	47.181	14.612
KP F-Statistic	35.788	80.958	69.447	48.316	47.419	87.605	42.534	62.688	66.940	37.074	50.501	55.234
N	131,893	131,893	131,893	192,952	192,952	192,952	76,137	76,137	76,137	41,498	41,498	41,498
Panel B: Only Major Activity												
$PM2.5\,(\mu g/m^3)$	0.006	0.001	0.001	-0.039	-0.095***	-0.002	-0.052	-0.139***	-0.000	0.026	-0.002	0.004
	(0.017)	(0.021)	(0.004)	(0.027)	(0.032)	(0.005)	(0.040)	(0.039)	(0.007)	(0.036)	(0.039)	(0.007)
Dep. Var. Mean	37.171	35.142	6.174	78.247	69.840	17.148	87.897	74.791	20.112	59.466	48.832	14.871
KP F-Statistic	35.788	80.958	69.447	48.316	47.419	87.605	42.534	62.688	66.940	37.074	50.501	55.234
N	131,893	131,893	131,893	192,952	192,952	192,952	76,137	76,137	76,137	41,498	41,498	41,498

Notes: Heteroskedasticity robust standard errors clustered by district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The dependent variable in all columns is the amount of time spent on outdoor activities. Activities classified as outdoor are discussed in the main text. Age restrictions for the sample are mentioned in the column header. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the Time Use Survey 2019.

Table C36: Intraday Heterogeneity by Industry Risk

	Low-risk			High-risk		
	7AM - 1PM	1PM - 7PM	7PM - 7AM	7AM - 1PM	1PM - 7PM	7PM - 7AM
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Both Major and Minor Activity						
$PM2.5\,(\mu g/m^3)$	-0.005	0.034	0.000	-0.091*	-0.255***	0.001
	(0.021)	(0.026)	(0.007)	(0.048)	(0.058)	(0.008)
Dep. Var. Mean	42.447	37.396	23.228	146.782	124.979	23.862
KP F-Statistic	59.431	64.099	68.456	57.834	47.523	78.847
N	53,946	53,946	53,946	118,163	118,163	118,163
Panel B: Only Major Activity						
$PM2.5\,(\mu g/m^3)$	-0.018	0.041	-0.001	-0.078	-0.261***	-0.003
	(0.023)	(0.027)	(0.007)	(0.048)	(0.060)	(0.009)
Dep. Var. Mean	43.557	38.374	23.918	152.075	129.491	24.471
KP F-Statistic	59.431	64.099	68.456	57.834	47.523	78.847
N	53,946	53,946	53,946	118,163	118,163	118,163

Notes: Heteroskedasticity robust standard errors clustered by district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. In all the columns, the sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. Additionally, the sample is restricted to those respondents who report being employed as their usual principal activity status. In columns (1) - (3), the sample is restricted to industries that are classified as low-risk. In columns (4) - (6), the sample is restricted to industries that are classified as high-risk. This classification is discussed in the main text. The dependent variable in all columns is the amount of time spent on outdoor activities in minutes. Activities classified as outdoor are discussed in the main text. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C37: Access to Air Quality Information

	Baseline	No Monitor	Has Monitor
	(1)	(2)	(3)
Panel A: Both Major and Minor Activity			
$PM2.5\,(\mu g/m^3)$	-0.109***	-0.059	-0.096*
	(0.036)	(0.062)	(0.051)
Dep. Var. Mean	157.875	166.090	144.782
KP F-Statistic	133.151	158.488	391.060
N	314,125	193,022	121,103
Panel B: Only Major Activity			
$PM2.5\,(\mu g/m^3)$	-0.104***	-0.039	-0.100*
	(0.036)	(0.063)	(0.053)
Dep. Var. Mean	162.057	170.380	148.791
KP F-Statistic	133.151	158.488	391.060
N	314,125	193,022	121,103

Notes: Heteroskedasticity robust standard errors clustered by district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60. The dependent variable in each column is the amount of time spent on outdoor activities. Activities classified as outdoor are discussed in the main text. In column (2), the sample is restricted to districts that or their neighboring do not have an operating ground-based pollution monitor that measures $PM2.5$ concentration. In column (3), the sample is restricted to districts that or their neighboring district have an operating ground-based pollution monitor that measures $PM2.5$ concentration. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C38: Non-Linear Effects

	Baseline	$PM2.5 > 90$	$PM2.5 > 100$	$PM2.5 > 110$
	(1)	(2)	(3)	(4)
Panel A: Both Major and Minor Activity				
$PM2.5\,(\mu g/m^3)$	-0.109***			
	(0.036)			
$\mathbb{1}\,[PM2.5\,(\mu g/m^3) > 90]$		-9.941		
		(6.769)		
$\mathbb{1}\,[PM2.5\,(\mu g/m^3) > 100]$			-10.918*	
			(6.340)	
$\mathbb{1}\,[PM2.5\,(\mu g/m^3) > 110]$				-11.861*
				(6.079)
Dep. Var. Mean	157.875	157.875	157.875	157.875
KP F-Statistic	133.151	60.845	94.178	84.149
N	314,125	314,125	314,125	314,125
Panel B: Only Major Activity				
$PM2.5\,(\mu g/m^3)$	-0.104***			
	(0.036)			
$\mathbb{1}\,[PM2.5\,(\mu g/m^3) > 90]$		-7.453		
		(6.958)		
$\mathbb{1}\,[PM2.5\,(\mu g/m^3) > 100]$			-9.265	
			(6.553)	
$\mathbb{1}\,[PM2.5\,(\mu g/m^3) > 110]$				-10.605*
				(6.293)
Dep. Var. Mean	162.057	162.057	162.057	162.057
KP F-Statistic	133.151	60.845	94.178	84.149
N	314,125	314,125	314,125	314,125

Notes: Heteroskedasticity robust standard errors clustered by district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The dependent variable in each column is the amount of time spent on outdoor activities in minutes. Activities classified as outdoor are discussed in the main text. Column heading specify the threshold for the indicator variables in column (2) to (4). Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C39: Effect of Air Pollution on Visibility

	(1)
$PM2.5\,(\mu g/m^3)$	-0.011**
	(0.004)
Dep. Var. Mean	11.006
KP F-Statistic	79.357
N	46,811

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique district and survey date pair. The dependent variable in all columns is visibility in kilometers. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C40: Time Spent on Activities related to Health by Age

	Baseline (1)	Age $\leq$ 22 (2)	23 $\leq$ Age $\leq$ 45 (3)	46 $\leq$ Age $\leq$ 60 (4)	Age > 60 (5)
Panel A: Both Major and Minor Activity					
$PM2.5\,(\mu g/m^3)$	0.001	0.006*	-0.003	0.002	0.013
	(0.004)	(0.003)	(0.004)	(0.007)	(0.011)
Dep. Var. Mean	2.620	1.157	2.692	2.873	4.575
KP F-Statistic	133.151	70.478	116.748	74.315	104.925
N	314,125	131,893	192,952	76,137	41,498
Panel B: Only Major Activity					
$PM2.5\,(\mu g/m^3)$	0.001	0.005*	-0.004	0.001	0.015
	(0.004)	(0.003)	(0.004)	(0.008)	(0.012)
Dep. Var. Mean	2.761	1.212	2.845	2.999	4.733
KP F-Statistic	133.151	70.478	116.748	74.315	104.925
N	314,125	131,893	192,952	76,137	41,498

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents those who report their gender to be either male or female. In column (1), the sample is further restricted to respondents who are between the ages of 18 and 60. Column headers for other columns denote the age range of respondents who constitute the estimation sample. The dependent variable in all columns is the amount of time spent on health related activities in minutes. Activities classified as those related to health include the following three-digit activity codes: 135, 372, 412, 422, 431, 512, 941, 942, and 949. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C41: Heterogeneity by Usual Principal Activity Status and Gender

	Self-Employed		Regular Wage/ Salaried Employee		Casual Labor		Unemployed or Not in Labor Force	
	Male	Female	Male	Female	Male	Female	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Both Major and Minor Activity								
$PM2.5\,(\mu g/m^3)$	-0.189**	-0.065	-0.064	-0.004	-0.248**	-0.375**	0.001	-0.007
	(0.076)	(0.109)	(0.047)	(0.041)	(0.105)	(0.187)	(0.039)	(0.023)
Dep. Var. Mean	273.492	201.843	137.915	89.701	317.125	265.042	88.257	59.265
KP F-Statistic	50.810	68.598	106.641	78.599	55.650	101.439	43.188	91.475
N	60,970	18,586	35,678	10,318	36,099	10,458	23,591	118,425
Panel B: Only Major Activity								
$PM2.5\,(\mu g/m^3)$	-0.178**	-0.039	-0.059	-0.014	-0.243**	-0.366*	-0.018	0.001
	(0.073)	(0.108)	(0.052)	(0.041)	(0.101)	(0.189)	(0.040)	(0.023)
Dep. Var. Mean	283.383	207.006	142.747	91.291	328.943	271.351	91.928	57.969
KP F-Statistic	50.810	68.598	106.641	78.599	55.650	101.439	43.188	91.475
N	60,970	18,586	35,678	10,318	36,099	10,458	23,591	118,425

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The dependent variable in all columns is the amount of time spent on outdoor activities in minutes. Activities classified as outdoor are discussed in the main text. The column headings indicate the subpopulation. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.

Table C42: Robustness to Adding Industry Codes

	Baseline (1)	Add NIC 2008 Codes (2)
Panel A: Both Major and Minor Activity		
$PM2.5\,(\mu g/m^3)$	-0.109***	-0.174***
	(0.036)	(0.056)
Dep. Var. Mean	157.875	235.269
KP F-Statistic	133.151	111.340
N	314,125	172,109
Panel B: Only Major Activity		
$PM2.5\,(\mu g/m^3)$	-0.104***	-0.164***
	(0.036)	(0.056)
Dep. Var. Mean	162.057	243.290
KP F-Statistic	133.151	111.340
N	314,125	172,109

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The dependent variable in all columns is the amount of time spent on outdoor activities in minutes. Activities classified as outdoor are discussed in the main text. The column header shows the specification type. Each specification in all columns includes weather controls, district and calendar date fixed-effects. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables are interactions of the district clusters and 30-degree wind direction bins for the district. Districts are classified into forty clusters based on their centroids. The sample contains data from the India Time Use Survey (ITUS) 2019.