Air Pollution and Time Use: Evidence from India*

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Abstract

We investigate how air pollution impacts outdoor activity avoidance, leveraging changes in local wind direction in an instrumental variable setup for causal identification. Our findings reveal a substantial reduction in time spent outdoors during polluted days, mainly driven by decreased engagement in employment-related activities. This effect varies significantly across age, education level, usual principal activity status, and residential location. Moreover, reduced outdoor time due to air pollution can potentially promote a more equitable allocation of unpaid caregiving responsibilities within households via increased male involvement. Our results rule out information provision as the primary mechanism and remain robust under various sensitivity tests.

JEL Classifications: D13, J17, J22, J46, O13, O15, 017, Q53, Q56

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1 Introduction

While the effects of air pollution on health and non-health outcomes are widely documented in both developing and developed country contexts, we know much less about the response of exposed individuals to elevated levels of air pollution. If these responses take the form of changes in routine behavior, then there might be substantial costs that are not quantified. Further, these changes might also affect quotidian interactions. For instance, more time indoors might affect the intrahousehold allocation of tasks between different members of the household. To the extent that these changes take the form of labor market adjustment, the preexisting distortions in these markets may get amplified.

Existing works examining the effect of air pollution exposure on behavior are almost exclusively based in the United States. The findings from these studies are unlikely to extrapolate to developing country settings due to multiple reasons. First, the information on air pollution is only sparsely available in developing countries. Therefore, citizens in such countries do not have enough information about their air pollution exposure and may not react efficiently to elevated levels of air pollution. Second, even if the information on air quality is readily available, prevailing socioeconomic conditions may drive a wedge between developed and developing country citizens' response to elevated pollution levels. Third, 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. In this paper, we, therefore, examine if and how elevated levels of air pollution affect avoidance behavior in a developing country context.

We measure avoidance behavior through time spent on activities that are performed outdoors. While being an imperfect measure of avoidance behavior, in the absence of detailed information on actions undertaken by the residents of more polluted areas, time spent on outdoor activities provides a reasonable proxy for the avoidance behavior. Inasmuch as the time reallocation does not capture all the aspects of avoidance behavior, the data limitation is compelling us to discover the lower bounds of the true effect. Further, due to high costs that are often associated with reducing time spent outdoors in developing countries where many industries consist of occupations where tasks are almost exclusively performed outdoors, reducing time spent outdoors may entail substantial pecuniary costs. Since the effect of air pollution exposure on various outcomes is net of these costs emanating from avoidance behavior, failure to properly account for them leads to an underestimation of the costs associated with air pollution exposure. Our setting is India, where these costs might be more acute due to the large share of the labor force employed in sectors where the work is chiefly done outdoors and ambient air quality is significantly worse than in developed countries.

We use large nationally representative time-use survey data from India. Using data from the India

Time Use Survey (ITUS), which collected information on time spent on various activities in 2019, we study how time-use patterns change on exposure to elevated levels of air pollution. ITUS collected detailed information on time spent on various activities for all household members who are six years of age or above. Information on activities performed in each 30-minute interval between 4 A.M. the day before the survey and 4 A.M. the day of the survey is collected. To classify activities into different categories, ITUS uses activity classification from the 2016 International Classification of Activities for Time Use Statistics (ICATUS). Activities are classified into 165 distinct categories, which provide us with detailed information on the activities performed by the household members. Using the description of activities, we classify an activity as being performed indoors or outdoors. We rely on the categorization of activities as indoor or outdoor proposed by Graff Zivin and Neidell (2014). Specifically, we only classify an activity as being performed outdoors if it is unambiguously performed outdoors[1]. We are, therefore, able to construct a measure of time spent on activities that are performed outdoors for each household member on which time-use information is available. We then combine these data with the data on air pollution and weather conditions, which we describe below using information on the district in which the household resides. To examine if individuals who are exposed to higher levels of ambient air pollution levels undertake avoidance behavior, we examine if time spent on activities that are performed outdoors changes when air pollution levels increase. We restrict the main estimating sample to respondents who are at least 18 years of age and not more than 60 years of age. Respondents in this age group are more likely to be actively participating in the labor market and have a greater say in how they allocate their time to various activities performed throughout the day.

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. These data provide comprehensive and continuous information on air pollution and weather conditions at a high spatial and temporal resolution. We construct air pollution concentration and weather conditions measures by taking the average of the measures that fall within the time window for which the time-use is reported. Our main pollutant of interest is $PM_{2.5}$. These are particulate matter that are 2.5 micrometers and 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 visually perceptible. This may prompt residents of the polluted area to change their time allocation to various activities, especially those that are performed outside. This study aims to empirically test this hypothesis.

[1]The description of activities classified as outdoors is presented in Table 1.

To uncover the causal effect of air pollution exposure on time-use patterns, we use an instrumental variables (IV) setup. Using existing work that leverages changes in local wind directions to instrument for air pollution concentrations, we instrument for district-level $PM_{2.5}$ concentration measure by an interaction of the district to be in one of the district clusters and the wind direction to be in one of the four 90° bins (Deryugina et al., 2019). By leveraging changes in the ambient air pollution levels that are driven by sources further away and hence affecting all districts in a cluster similarly, we are able to abstract away from the need to have information on the precise location of local polluting sources. For our instruments to be valid, we need changes in local wind directions to be orthogonal to the residual variation in time-use patterns after accounting for a battery of fixed-effects and demographic controls. While our data precludes us from directly testing this assumption, through multiple falsification checks, we establish the validity of our instruments. We also show that for our main specifications, instruments based on wind directions have a strong first-stage.

Our point estimates from the preferred IV specifications 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 seven minutes, or a 4.4% decline in time spent on activities that are performed outdoors over the sample mean (2.6 hours). High first-stage F-statistic suggests that our instruments predict $PM_{2.5}$ concentrations reasonably well. We also show that our main effect of a decline in the time spent on activities that are performed outdoors (baseline or main effect hereafter) is not driven by restrictions on our main estimating sample. We show that the point estimates from the baseline specifications are unaltered from restricting the sample to days that the survey considers as "normal", dropping extreme values of time spent on activities that are performed outdoors, extending the sample to include all the members of the surveyed households who are above the age of six. We establish that our main effects are not conflated by the non-random selection of households for interview on more polluted days, the presence of pollutants other than $PM_{2.5}$, and using a larger number of clusters to which the districts can be assigned in the IV setup. We further show that the short-run effect of reduced time spent on activities that are performed outdoors is due to exposure to contemporaneous air pollution levels and not due to its lag or lead.

We also find that the main (baseline) effect of reduced time on activities that are performed outdoors is more pronounced for respondents who identify as male, residents of rural areas, and households who are relatively worse off in terms of socioeconomic status. It is worth emphasizing that almost all of the decline in time allocated for outdoor activities results from the drop in time spent on employment-related activities - a robust verdict irrespective of the sampling restrictions we impose upon age intervals. Further, we find that this reduced time spent on activities that are performed outdoors and are related to employment is reallocated to indoor leisure[2] and outdoor unpaid care activities[3]. These findings imply that elevated levels of air pollution might lead to more equitable intrahousehold distribution of activities related to unpaid care. We find that on more polluted days, the share of male members' time spent on activities that are performed outdoors and are related to unpaid care increases. This finding is further bolstered by a more pronounced decline for single-member households. We observe that 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-related outdoor activities.

Our investigation reveals a monotonic decline in the baseline effect with education level. The effect of air pollution exposure on time allocated for outdoor activities is most pronounced for respondents who are illiterate, while this effect is absent for respondents who have completed college. We interpret this result in the backdrop of employment of college-educated population in jobs that do not provide a margin for flexible labor supply. Therefore, given that most of the decline in the main findings comes from the activities related to employment, we would reckon to see no effect on college-educated. Additionally, we comprehend that the main effect is more pronounced for respondents who report being self-employed or casual labor as their usual principal activity status. Respondents with these usual principal activity statuses are more likely to have flexible work schedules with relatively more freedom over the labor supply decisions in the short-run. Therefore, we would expect to see a more pronounced effect on these subpopulations. The absence of effect on time spent on activities that are performed outdoors for respondents who report regular wage or salaried employee and unemployment as their usual principal activity status ties well with the reduced time being mostly driven by employment-related activities that are performed outdoors as the absence of flexibility in labor supply decisions in the short-run for this subpopulation does not provide enough margin to reallocate time use on activities that are performed outdoors and are related to employment.

We discover that our main effect of the decline in time spent on activities that are performed outdoors is driven entirely by the industries that are classified as being high-risk (Holub and Thies, 2022). These industries are those where a typical employee spends most of the time on work outdoors. Given that the main effect of the decline in time spent on activities that are performed outdoors is driven by the respondents who have flexible labor supply arrangements, we should not expect to see any difference in the effect of air pollution exposure on time spent on activities that

[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.

[3]Unpaid care activities include unpaid caregiving and domestic services for household and family members, as well as unpaid volunteer, trainee and other unpaid work.

are performed outdoors among different days of the week. Our results support this hypothesis as we fail to detect any significant difference in the effects across different days of the week. We also do not detect a significant difference in the main effect due to better information provision about air quality. In other words, we do not observe any difference between districts with and without an operating ground-based air pollution monitor. We also find weak evidence for the non-linear effects of air pollution exposure on time spent on activities that are performed outdoors.

The closest to our work is Bäck et al. (2013), Graff Zivin and Neidell (2009), and Neidell (2009). All three studies are based in the United States. Using data from the American Time Use Survey, Bäck et al. (2013) find that higher pollution levels are associated with less time spent outdoors but only for some sensitive groups. Leveraging changes in the color codes used for air quality information in a regression discontinuity framework, these authors do not find any change in time spent outdoors for any subgroups. Their conclusions, hence, echo our null finding on the information provision as the likely channel leading to the causal impact of air pollution on avoidance. Graff Zivin and Neidell (2009) rely on data on attendance from two outdoor venues to study if attendance changes when smog alerts are issued. These authors leverage the issuance of smog alerts, which are issued when the air quality index crosses a particular threshold in a regression discontinuity framework. They find that attendance goes down by up to 15% when the alerts are issued for one day only, with this effect dampening if the alerts are issued for two consecutive days and becoming zero when an alert is issued for three consecutive days. Using the same setting as in Graff Zivin and Neidell (2009), Neidell (2009) shows that people respond to smog alerts by reducing time spent outdoors. The author also shows that failure to account for avoidance behavior leads to a downward bias in the estimated effects of air pollution exposure on asthma-related hospitalizations.

Our work differs from these studies in multiple ways. First, our context is India, which has much higher levels of baseline ambient air pollution levels. To the extent that there are non-linearities in the response function of time-use to air pollution concentrations, the estimates from these studies might not be a reliable guide in more polluted settings. Second, we do not restrict our sample to sample geographical settings. We use data on all districts in India to provide a nationwide estimate of the effect of air pollution exposure on time-use. Third, due to the large sample size, we have enough statistical power to document changes in time allocation to not only different activities but also whether this allocation is differentially affected for various subpopulations. Finally, we leverage different plausibly exogenous changes in air pollution levels to identify the effect of air pollution exposure on time-use patterns.

With this work, we contribute to multiple strands of literature. First, we contribute to a nascent and active literature on the effect of air pollution exposure on avoidance behavior (Bäck et al., 2013; Graff Zivin and Neidell, 2009; Ito and Zhang, 2020; Neidell, 2009; Saberian et al., 2017; Wang and Zhang, 2023). Building on these existing works that almost exclusively rely on small geographical areas, we provide nationwide estimates of the effects of air pollution exposure on time spent outdoors. Further, 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. Second, we contribute the literature that examines the effect of exposure to short-run changes in weather 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 pollution. Third, we contribute to the literature on the time use patterns in developing countries (Field et al., 2023; Hirway, 2010). We add to this literature by showing that male members of households increase their time allocation to unpaid care activities on more polluted days, which in turn increases time-use for leisure activities by female members of the household. Therefore, although air pollution exerts large negative effects on various outcomes, it might have an unintended consequence of making time allocation on unpaid activities within the households more equitable. Fourth, we contribute to a large literature studying myriad effects of air pollution exposure in developing countries (Aguilar-Gomez et al., 2022; Greenstone and Jack, 2015). Finally, this paper is also related to a large literature on determinants of labor supply (Behrman, 1999). To this literature, we add findings from a developing country for the effect on labor supply due to plausibly exogenous increases in air pollution.

The rest of this paper is organized as follows. In Section 2, we discuss the data we use and also provide summary statistics for our analytical sample. In Section 3, we discuss our empirical strategy and also discuss threats to identification. We then present results in Section 4. Section 5 provides a discussion of our findings and concludes.

2 Data

The ideal individual-level data to study the effect of contemporaneous air pollution exposure on avoidance behavior in terms of time allocations on various activities will contain the information on each person's individual and household characteristics, their full 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 a nationally representative India time-use survey (ITUS) in 2019. We rely on satellite reanalysis data to obtain the information on air pollution and weather conditions. In what follows, we describe time-use and satellite reanalysis data in detail by presenting 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) 2019

We use a nationally representative time-use survey from India conducted in 2019 to obtain time-use information. ITUS is collected by the Indian National Sample Survey Organization (NSSO) and surveyed all individuals aged six years and above in 138,799 households. In total, 447,250 individuals were surveyed between January and December 2019. Information on time-use for a 24-hour period is collected starting from 4 A.M. on the day before the date of the interview to 4 A.M. on the date of the interview. This 24-hour period is further split into 48 time slots of 30 minutes duration each. Each respondent is asked about the activities they performed in each time slot. In case the respondent performs multiple activities in a given time slot, all activities that were performed for 10 minutes or more are recorded. 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 approach assigns the entire duration of the time slot to the reported major activity. The second approach 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 "major" and "both major and minor" activities, respectively. In order to classify the activities into various categories, we integrate 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 of the household members. Usual principal activity status contains information on whether the household member is employed, unemployed, or not in the labor force. Additionally, we also 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 household member spends on activities that are performed outdoors. To classify activities as being performed outdoors, we use the description of all three-digit activities in ICATUS. 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 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 classifed hereby activities as outdoors in Table 1. We note that the household members allocate a large fraction of the time spent outdoors on production of goods [and services] either for own final use or in household enterprises, whereas some fraction is allocated for leasure activities. For the activities that are equivocal in description whether they are performed outdoors, indoors or the combination of both, we will recover a lower bound on the negative effect of air pollution exposure on time spent on activities that are performed outdoors.

2.2 Satellite Reanalysis Data

In order to obtain information on air pollution exposure of household members, we make use of satellite reanalysis data. To construct air pollution measures, 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. These data are available at a high spatial and temporal resolution. In particular, we use data that has a horizontal resolution of approximately 80 km ($0.75^\circ \times 0.75^\circ$) 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., 2023). In order 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; Pullabhotla and Souza, 2022). It should be noted that satellite reanalysis data have been shown to underestimate the actual pollutant concentrations at higher levels (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 is an underestimate of the true effect of air pollution exposure on time spent outdoors. In Figure 1, we show that the CAMS-EAC4 satellite reanalysis data that we use for our main specifications correlates well with ground-based monitor data. As discussed in Section 1, our main pollutant of interest is $PM_{2.5}$. We also show that other results are not confounded due to the presence of other pollutants that may be correlated to $PM_{2.5}$ concentrations. We obtain information on these other pollutants, namely ozone, nitrogen dioxide, and sulfur dioxide, from CAMS EAC4 data.

In order to control for weather conditions that can jointly affect time-use and air pollution levels, we obtain information on weather conditions from ERA5-Land climate reanalysis data (Connolly, 2008; Garg et al., 2020; Graff Zivin and Neidell, 2014; Muñoz Sabater et al., 2021). These data have been extensively used for obtaining information on weather conditions in a wide variety of contexts. These data are derived from satellite reanalysis where the forecast models are tuned with the available observational data on climatic conditions (Parker, 2016). These data are available at a high spatial and temporal resolution. In particular, we use data that has a horizontal resolution of approximately 9 km ($0.1^\circ \times 0.1^\circ$) and hourly temporal resolution. We use data on temperature, precipitation, and wind speed.

2.3 Analytical Sample Construction

In this subsection, we describe 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 district as the spatial unit. We use information on the district of residence for the household in the ITUS data. To construct district-level measures of air pollution concentrations and weather conditions, we use district-level shapefiles. These district-level shapefiles data come from the Housing and Population Census of 2011. It should be noted that ITUS data is collected in 2019 when many new districts have formed since 2011. In order to obtain information on all districts that we observe in the ITUS data, we manually determine the parent district in 2011 shapefiles data for each district that is newly created between 2011 and 2019. We are, therefore, able to 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, with the only difference being that we average all 24 hourly measures within the relevant 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. This precludes us from being able to obtain pollution exposure information for these households. Therefore, in our analysis, we drop observations on these households.

2.4 Descriptive Statistics

In this subsection, we discuss descriptive statistics for our main analytical sample. We start by presenting basic descriptive statistics for the individual- and household-level variables that we observe in our data. We present the number of observations with non-missing information, mean, standard deviation, minimum value, and maximum value for each variable. These are presented in Table 2. In order to account for complex survey design, we weight observations using the weights that the National Sample Survey Organization (NSSO) provides in the survey data. Our analytical sample is evenly distributed between males and females, with three-fourths of the respondents being married at the time of the survey. We also note that more than three-fourths of the respondents are literate. ITUS considers a respondent to be literate if they are able to read and write a simple message with understanding in at least one language. 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. We note that almost 34 % of the respondents are housemakers and attend to domestic duties full-time. Next, we discuss household-level variables. The average household has approximately four members, and almost 82 % of the households practice Hinduism. Later, we examine if the effect of air pollution exposure on time spent on activities that are performed outdoors differs across these subpopulations.

We now discuss the spatial and temporal variation in the time-use patterns and air pollution concentrations that we leverage to estimate the causal effect of air pollution exposure on time spent on activities that are performed outdoors. In Figure 2, we present the mean $PM_{2.5}$ concentration and associated 95% confidence intervals for each day of the year. We conclude 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, while winter months have elevated air pollution concentrations. In our empirical strategy, we explicitly account for this seasonality in air pollution concentrations. In Figure **??**, we present the spatial variation in our air pollution measure as well as the time spent on activities that are categorized as being performed outdoors. We note that the Indo-Gangetic plains have high levels of air pollution. In the second and third subfigure, we see that time spent on activities performed outdoors is also lower in this region relative to other less polluted regions of the country.

In Table 3, we show the average time spent on activities classified as being performed indoors or outdoors depending on whether the air pollution concentration is below or above 100 $\mu g/m^3$. With this statistic, we aim to examine if there is a decline in the time spent on activities performed outdoors when the pollution is high outside. As we see in the second and fourth columns of the table, time spent on activities performed outdoors on average is 21 minutes lower on more polluted days relative to days when air pollution concentrations are lower. In what follows, we examine if this decline in the time spent on activities performed outdoors can be given a causal interpretation. In the next section, we outline the empirical strategy that we adopt to this end.

3 Empirical Strategy

In this section, we discuss our empirical strategy. We start by detailing a fixed-effects specification, which we estimate using OLS estimation. We then discuss why this specification might produce biased estimates. To uncover consistent estimates of the effect of air pollution exposure on time spent on various activities, we detail an instrumental variables (IV) setup and discuss identification along with estimation of this specification. We briefly then discuss threats to identification in our instrumental variables setup.

We estimate the following specifications using OLS.

$$y_i = \alpha_{i(d)} + \alpha_{i(t)} + \beta PM2.5_{i(d,t)} + \mathbf{X}_i\gamma + \mathbf{X}_{i(h)}\delta + \varepsilon_i \tag{1}$$

This specification includes fixed-effects for the district of residence and time. Time fixed-effects, $\alpha_{i(t)}$, enter the specification through fixed-effects for day-of-year and day-of-week. District of residence fixed-effects, $\alpha_{i(d)}$, control for time-invariant district-level observable and unobservable characteristics. These factors, for instance, include the topography of the district. Time fixed-effects control for observable and unobservable factors that are common to all districts. These include factors like big national sports events that affect time-use. Failure to account for both these sets of fixed-effects will confound our estimates as we will misattribute the effect of such factors on time-use to air pollution. Equation (1) also controls for individual- and household-level controls. Individual-level controls, denoted by vector $\mathbf{X}_i$, include age, gender, highest education level, and usual principal activity status. Household-level controls, denoted by $\mathbf{X}_{i(h)}$, include the number of members in the household, religion, usual monthly consumption expenditure, social group, and primary source of energy for cooking. In Equation (1), y_i is the outcome of interest. In almost all specifications, this is the amount of time spent on various activities. When this is not the case, we detail what the outcome variable is when we discuss results later. In Equation (1), 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. Our parameter of interest in Equation (1) is β. This gives the marginal effect of a unit change in $PM_{2.5}$ concentration on the outcome variable.

While specification in Equation (1) leverages within district overtime changes in air pollution levels after purging out the effects of secular shocks and observable individual- and household-level observables, the estimated effect of air pollution exposure on time spent on various activities may still be biased. This could happen due to either omitted time-varying variables (OVB) that we cannot account for or due to measurement error in the air pollution exposure. While we assign district-level air pollution levels to all households in a given district, this may not be the correct measure of air pollution exposure for members of that household. Plausibly, air pollution varies a lot within districts, thereby leading to measurement errors in our pollution concentration measure. As long as measurement error in air pollution concentrations is not systematically related to time-use patterns, our estimated effect of air pollution exposure on time spent on various activities will be an underestimate of the true effect. OVB might also lead to biased estimates of the effect of air pollution exposure on time-use patterns. Apriori, it is uncertain which way the estimated effects will be biased. For instance, crop residue burning entails field activity that is done outdoors and also increases air pollution levels. Such incomprehensible factors would lead us to overestimate the effect of air pollution exposure on time spent outdoors. On the other hand, observance of religious festivals with fireworks leads to less time spent outdoors but increases air pollution levels, thereby leading to an underestimation of the true effect of air pollution exposure on time spent outdoors.

To assuage concerns related to the endogeneity of air pollution measures, we turn to an instrumental variables setup. We rely 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 instrumental variables setup using the following first-stage specification.

$$PM2.5_{i(d,t)} = \alpha_{i(d)} + \alpha_{i(t)} + \sum_{k=1}^{40}\sum_{b=2}^{4} \theta_{k,b} \mathbb{1}\left(i\left(d\right) \in k\right) \times \mathbb{1}\left(w_{i(d,t)} = b\right) + \mathbf{X}_i\gamma + \mathbf{X}_{i(h)}\delta + \mu_i \quad (2)$$

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 residence d to be in cluster k, $\mathbb{1}\left(i\left(d\right) \in k\right)$, and wind direction for the district of residence d on the date of survey t to be in bin b, $\mathbb{1}\left(w_{i(d,t)} = b\right)$. Using the k-nearest neighbors algorithm, we cluster districts into 40 clusters. This non-parametric supervised learning classifier uses 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 estimable. We, therefore, use the k-nearest neighbors algorithm to optimally trade off reduced variance and increased bias by classifying multiple districts in the same cluster. We later establish the robustness of our results by using different numbers of clusters to which the classifier can classify districts. In Figure **??**, we show the cluster to which each district in our cluster is assigned. We use four wind direction bins, each of 90° interval. The omitted wind direction bin is $[0^\circ, 90^\circ]$. In all our IV specifications, we present first-stage F-statistics to establish the strength of our excluded instruments.

To identify the causal effect of air pollution exposure on time spent on various activities, the instruments should affect time-use patterns only through their effect on air pollution concentration, thus affording the exogoneity assumption. We present multiple falsification checks to establish the validity of our instruments. Since the instruments affect 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 local time-varying unobservables that jointly affect time-use patterns and air pollution levels. Further, in our setup, the same wind direction can affect wind direction differentially in different district clusters. Since we use two-stage least squares estimation for our IV specifications, the second-stage is given by the following specification.

$$y_i = \alpha_{i(d)} + \alpha_{i(t)} + \beta P\hat{M}2.5_{i(d,t)} + \mathbf{X}_i \gamma + \mathbf{X}_{i(h)} \delta + \nu_i \tag{3}$$

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 $P\hat{M}_{2.5}$. We next discuss results from estimating Equation (1) - (3) for various outcome variables. Wherever necessary, we also detail other specifications that we estimate that are not a variant of these equations.

4 Results

4.1 Main Results

We start by presenting results for our main specifications in Table 4. We present results from both an OLS estimation of Equation (1) and two-stage least squares estimation in Equation (2) - (3). We also present results for both approaches of calculating time spent on an outdoor activity in a given time slot. In the top panel, multiple activities in a given time slot are assigned equal time. In the bottom panel, however, only a major activity is assigned the entire time duration for a given time slot over which the respondent reports various activities. As we move across the table, we employ more 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 day-of-week and day-of-year fixed-effects to identify the effect of air pollution exposure on time spent on activities that are performed outdoors. In our preferred specifications in the last two columns, (8) and (9), 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. Namely, the marginal effect of a 1 microgram per cubic meter increase in the pollutant concentration is nearly 0.094 minutes reallocated from outdoor to indoor activities, *ceteris paribus*. This is equivalent to a decline of approximately seven minutes in time spent on activities that are performed outdoors. This corresponds to an approximately 4.4% decline in time spent on activities that are performed outdoors over the sample mean. 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. Given the results, we fancy IV estimates over OLS as long as the latter suffers from potentially positive omitted variable bias. In an alternate, less demanding specification in columns (6) and (7), we exclude day-of-year fixed-effects. While slightly larger in magnitude, point estimates from these specifications are very close to point estimates from our preferred specifications in the last two columns. We also note that the results in both the top and bottom panels are similar, albeit the bottom panel has slightly attenuated effects of air pollution exposure on time spent on activities that are performed outdoors.

4.2 Robustness Checks

Next, we turn to establish the robustness of our main finding of a reduction in time spent on activities that are performed outdoors. In Table 5, we present the robustness of our results using alternate samples. We note that the specifications estimated for the point estimates in this table are still given by Equation (1) - (3). We only change the sample on which these specifications are estimated. In the first two columns of the table, we repeat our baseline estimate from the preferred specifications in the last two columns of Table 4. In the next four columns, we use information on the type of the day for which the respondent reports the time spent on various activities. ITUS classifies a day for which the time diary is reported as either "normal" or "other". A day is designated as "normal" if the respondent performed routine activities. If, due to any reason, the respondent is unable to 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. Our point estimates suggest that the main effect is not sensitive to restricting the sample to only "normal" days. The point estimates in columns (3) and (4) are very close to the point estimates in the first two columns. In columns (7) and (8), we drop observations for which the respondents report spending time outdoors, which is above the 95th percentile of the sample distribution of time spent on activities performed outdoors. 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 on activities outdoors. While our results are attenuated relative to the baseline when we drop these extreme observations, we continue to find statistically significant declines in outdoor activities on more polluted days. In the next two columns, columns (9) and (10), we show that our main effect is robust to the inclusion of all the members of the households who are above the age of six years, irrespective of their reported gender. We find attenuated effects of air pollution exposure on time spent on activities performed outdoors, although this effect continues to be statistically significant. Finally, in the last two columns of Table 5, we use an alternate data source to construct measures of $PM_{2.5}$ concentration. We use a measure derived from MERRA-2 satellite reanalysis data. While our point estimates of the effect of air pollution exposure on time spent on activities performed outdoors are no longer statistically significant, we continue to find negative effects of air pollution exposure on time spent on activities that are performed outdoors. We highlight that the IV point estimates are many times larger than the OLS point estimates when we use MERRA-2 data. This might be due to the relatively imprecise and noisier measure that we derive from this alternate data source to construct air pollution concentration measures. We note that the aforementioned 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. Overall, results in Table 5 help us conclude that our main effect is robust to various changes we make to the estimating sample.

Our empirical strategy leverages variation within districts in the interviews conducted on days with different levels of pollution. To the extent that the number of interviews differs across less and more polluted days, our estimates might be biased by 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. For each day during which interviews are conducted in our sample, we construct a measure with 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, day-of-week, and day-of-year 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 6. We find no effect of air pollution levels on the number of interviews conducted in the district. This 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 our point estimates might be conflated by the effect of other pollutants on time spent on activities that are performed outdoors. We first replace the $PM_{2.5}$ concentration levels with ozone, NO_2, and SO_2 concentrations in Equation (1) - (3). We also present results from a specification where we augment Equation (1) - (3) with concentration levels of these other pollutants. We note that the data from these pollutants is derived from CAMS-EAC4, the same data source that we use to construct our measures of $PM_{2.5}$ concentrations. We present results from these specifications in Table 7. We conclude that our main effects are not confounded by the presence of other pollutants that might be correlated with $PM_{2.5}$. In Table A1, we establish that our main effect of reduced time on outdoor activities is similar across particulate matter of different sizes.

We examine if our main effects are altered by the number of clusters that we use to assign districts to the clusters. Recall that in our main specification, we restrict the number of clusters to which the districts can be assigned to 40. We examine if the greater number of clusters to which the districts can be assigned substantially affects our point estimates. We present results from using the alternate number of clusters used to assign the districts in Table 8. Although our point estimates get attenuated when we use a greater number of clusters, we continue to find negative effects of air pollution exposure on activities that are performed outdoors. This suggests that our main effect is not driven by the number of clusters used to assign the districts. We also examine if a particular state is responsible for the effect of air pollution exposure on time spent on activities that are performed outdoors that we estimate. We present results from estimating our main specifications in Equation (1) - (3) on dropping one state at a time from the estimating sample in Figure 3. This figure shows that any particular state is not driving our main effect.

Next, we examine if alternative measures of uncertainty alter our results. Our main regressor, pollution concentration, is constructed at the district-level. In our baseline specification, we cluster standard errors at the district-level. Further, 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. We then estimate the baseline specifications with these measures. We repeat this process 500 times. We present the distribution of the point estimates on the pollution concentration measure variable from this bootstrapping approach in Figure 4. We see that none of the bootstrapped point estimates are lower than the point estimate from our baseline specification. We, therefore, conclude that our main effect is robust to the measure of uncertainty used for inference.

To conclude our discussion on the robustness of our main effects, we examine if controlling for air pollution lag and lead affects our main effect of air pollution exposure on time spent on outdoor activities. Earlier work examining the effect 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). We build on this existing work and examine if elevated pollution levels result in intertemporal reallocation of activities that are performed outdoors. We augment our specifications in Equation (1) - (3) by including lag and lead of $PM_{2.5}$ concentration. We instrument these air pollution measures with the corresponding district-level changes in wind direction. We present results from estimating these specifications in Table 9. We find that neither the lag nor the lead of air pollution concentration statistically significantly affects contemporaneous time-use on activities that are performed outdoors. The absence of effect on the lag of pollution measure is surprising as some activities are spread over multiple days in order 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 that are related to employment, we will expect that more flexible work arrangements dampen the intertemporal reallocation of time spent on outdoor activities.

4.3 Heterogeneous Effects

We now turn to discuss whether our main effect is heterogeneous across various subsamples. We start by examining the heterogeneous effect of air pollution exposure on time spent on activities that are performed outdoors by subpopulations defined by gender, rural-urban status, and usual monthly consumption expenditure. We estimate the same specifications as those in Equation (1) - (3). We restrict the estimating sample based on the categories mentioned above. We present results from these specifications in Table 10. We start by discussing whether the effect of air pollution exposure differs between those respondents who identify as either male or female. We present results for these subpopulations in the first four columns of Table 10. We find that the reduction in time spent on outdoor activities is more pronounced for those respondents who identify themselves as male relative to those who identify themselves as female. In the next four columns, we examine if the estimated effect of air pollution exposure on time spent on activities that are performed outdoors differs between the rural and urban status of the area where the respondent resides. We note that the ITUS defines rural as those villages that are inhabited. Urban areas are defined as towns and cities. Within a district, we observe respondents who reside in both rural and urban areas. Finally, in the last four columns of the table, we examine if the effect of air pollution exposure on time spent on activities that are performed outdoors differs between households that have below or above median usual monthly consumption expenditure (UMCE).

We find that our main effect is driven by the changes in time-use patterns due to exposure to elevated levels of air pollution for only those households that report below median UMCE. This finding echoes the findings in the previous four columns. Households in rural areas are also more likely to report UMCE, which is below the median. While only 33% of surveyed households residing in the urban areas report having a below median UMCE, this proportion is significantly larger for residents of rural areas at 62%. Overall, in this table, we show that the time spent on outdoor activities due to exposure to elevated levels of air pollution is reduced more for males, residents of rural areas, and households who are relatively worse off in terms of socioeconomic status.

Our point estimates suggest that our main effect is driven by residents of rural areas. This finding is par for the course provided the apparent socioeconomic gap between rural and urban areas, more flexible work schedules, and bigger share of self-employed and non-college degrees among rural populations in our context. While we are unable to test various mechanisms that might lead to this differential effect of air pollution exposure on time-use patterns between rural and urban areas, we later suggest potential channels through which this difference might result.

Now, we discuss 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 3-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 exhaustive groups. The first group consists of activities that are related to employment[4]. The second group consists of activities related to the production

[4]These activities are those whose first digit in the 3-digit activity code is one.

of goods for own final use[5]. The last two groups consist of activities related to unpaid services and leisure.[6] We present results from examining the differential effect of air pollution exposure on time spent on activities within these four groups in Table 11. We find that almost all of the decrease in time spent on activities that are performed outdoors results from employment-related activities. Further, we find that this reduced time is almost entirely reallocated to activities related to leisure that are performed indoors. The remaining time saved from reducing outdoor activities related to employment is reallocated to outdoor activities related to unpaid care. Later, we examine if this increased time allocation to activities performed outdoors related to unpaid care leads to intrahousehold substitution from females to males for these activities. We also show that the effect observed for outdoor activities related to employment is not driven by the respondents' age. In Table A2, we show that our result on employment-related outdoor activities is unaltered by using all the respondents who are above the age of six. Overall, the results in Table 11 suggest that on exposure to elevated levels of air pollution, people respond by reducing time spent outdoors on activities related to employment. Further, they reallocate this saved time to activities related to leisure that are performed indoors and activities related to unpaid care that are performed outdoors.

Next, we examine if the increase in time spent on activities related to unpaid care that are performed outdoors is reallocated between male and female members of the households. We restrict the estimating sample to the households that have at least one male and female member. We then construct a measure of male members' share of time spent on four broad groups of activities discussed previously for Table 11. We estimate household-level specifications with the same set of household controls and fixed-effects as those in Equation (1) - (3). The dependent variable in these specifications is the share of time male members of the household spent on various activity groups. We present results from estimating these specifications in Table 12. We find that the share of time male members of the households spent on activities related to leisure that are performed outdoors goes down. At the same time, we observe that the male share of time spent on outdoor activities related to unpaid care goes up.We exercise caution in interpreting these results as improved intra-household allocation of unpaid care services for female members as our estimates for activities related to unpaid care that are performed outdoors are sensitive to how the time in a given time interval is allocated between "major" and "minor" activities. Nonetheless, we do find robust evidence for increased time allocated for leisure activities performed outdoors for female members of the household relative to male members of the household. Overall, in a context where females bear the burden of providing unpaid care within the household, increased air pollution exposure might lead to a more equitable distribution of the burden related to the provisioning of unpaid care within

[5]These activities are those whose first digit in the 3-digit activity code is two.

[6]Activities for group based on unpaid care activities are those for whom the first digit of the 3-digit activity code is 3, 4, or 5. Whereas activities for the final group are those for whom the first digit of the 3-digit activity code is 6, 7, 8, or 9.

the household (Vyas, 2021). 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 inasmuch as the offset due to the time spent outdoors for unpaid care is non-existent for single-member households. We examine this hypothesis in Table 13. We estimate specifications similar to those in Equation (1) - (3). We, however, change the estimating sample by restricting the main estimating sample to either members in multiple-member households or single-member households only. We find that the decline in time spent on activities that are performed outdoors is more pronounced for single-member households than for households with multiple members. We, nonetheless, exercise caution in emphasizing this result due to the worsened performance of the instruments in predicting air pollution concentrations in the first-stage. The pronounced effect of air pollution exposure on time spent on activities performed outdoors for single-member households is consistent with intrahousehold reallocation of activities related to the provisioning of unpaid care that are performed outdoors between male and female members of the household.

We now discuss if the effect of air pollution exposure on time spent on activities that are performed outdoors differs by the age of the respondent. We estimate specifications in Equation (1) - (3) but change the estimating sample. We create four mutually exclusive and exhaustive groups with different age intervals of the respondents. The first group consists of all respondents who are six years of age and above 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 and are actively participating in the labor market. The third group consists of respondents who are between the ages of 46 and 60 years of age. The final group consists of respondents who are above the age of 60. We present results from estimating the specifications that we outlined above for these four groups in Table 14. We find that our main effect of reduction in time spent on activities that are performed outdoors is driven by the decline in time spent on activities that are performed outside by the group of respondents who are more likely to be participating in the labor market. We do not find a statistically significant effect for respondents who are either 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 11. Since the baseline effect is mainly driven by employment-related activities, the heterogeneous effect for active labor market participats verifies the logical double-checking.

We next turn to discuss if our main effect of reduced time spent on activities that are performed outdoors is driven by respondents with different levels of education. We restrict our estimating sample to those who are above the age of 23 years and thus more likely to have completed their education. We estimate the specifications in Equation (1) - (3) for this restricted sample. 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 that are performed outdoors differs between these groups. The first group consists of respondents who are coded as being not literate in the survey. ITUS considers a respondent to be literate if they are able to read and write a simple message with understanding in at least one language. The second group of respondents consists of respondents who have completed up to primary school education. The third and fourth group of respondents consists of those respondents who have completed above primary school and college, respectively. We present the results in Table 15. We find that the effect of air pollution exposure on time spent on activities that are performed outdoors monotonically decreases as the level of education of the respondent increases. The most pronounced effect is found for respondents who are illiterate. The effect of air pollution exposure on time spent on activities that are performed outdoors is not statistically significant for respondents who have completed college. We interpret this finding against the backdrop of high returns to college education in the labor market in our context. As we later discuss, the decline in time spent on activities that are performed outdoors due to elevated levels of air pollution exposure is driven by respondents who have flexibility in their labor supply. Since most college educated individuals in our context are employed in the formal sector with quite stringent working requirements, the absence of the effect is anticipated.

We next discuss if the effect of air pollution exposure on time spent on activities that are performed outdoors differs by the usual principal activity status of the respondent. Usual principal activity status contains information on whether the household member is employed, unemployed, or not in the labor force. For those respondents who are employed, we construct three mutually exclusive and exhaustive groups. We classify a respondent who is employed as defined by the usual principal activity status to be either self-employed, regular wage or salaried employee, and supplying casual labor. We combine respondents who are unemployed or not in the labor force in a single group. We estimate specifications in Equation (1) - (3) with respondents in these groups as part of our estimating sample. We present results in Table 16. Our results show that our main effect is driven by respondents who report their usual principal activity status to be either self-employed or supplying casual labor. Respondents with these usual principal activity statuses are more likely to have flexible work schedules with relatively more freedom over the labor supply decisions in the short-run. Therefore, we would expect to see a more pronounced effect on these subpopulations. As we discussed above, the absence of a statistically significant effect for regular wage or salaried employees echoes our previous results. The absence of flexibility in labor supply decisions in the short-run for this subpopulation does not provide enough margin to reallocate time spent on activities that are performed outdoors and related to employment. Since the decline in time spent on activities that are performed outdoors is driven by activities that are related to employment, we would not expect to see air pollution affecting time spent on these activities for regular wage or salaried employees.

We now discuss if our results differ by the risk of outdoor exposure of industries in which the respondents are employed. We estimate the specifications in Equation (1) - (3). We use the information on the industry of work for those 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 2-digit codes for the industry of employment of the respondents. We rely on the high-risk classification of industries in Graff Zivin and Neidell (2014). We treat an industry to be high-risk if it is related to either of agriculture, forestry, fishing and hunting, mining, construction, manufacturing, transportation, and utilities. We present results in Table 17. We find that our main effect of reduction in time spent on activities that are performed outdoors is driven entirely by the industries that are classified as being high-risk. We do not find any statistically significant effect of air pollution exposure on time spent on activities that are performed outdoors for respondents who are employed in low-risk industries. Since the employed respondents in the high-risk industries are most likely to be exposed to air pollution, the estimated effects for this subpopulation are straight-forward.

We now turn to discuss if our estimated effect of air pollution exposure on activities that are performed outdoors differs by the day of the week on which the time diary is recorded. We estimate specifications in Equation (1) - 3 but restrict the estimating sample to those respondents who are interviewed on a given day of the week. We present results in Figure 5. Point estimates from our preferred IV specifications suggest that there is no significant difference in the effect of air pollution exposure on time spent on outdoor activities by the day of the week on which the time diary is recorded. This finding connects well with our previously discussed results. We showed that the decline in the time spent on activities that are performed outdoors is driven by those respondents who are self-employed or employed as casual laborers. As respondents in these employment categories are likely to have no binding constraint in terms of when they can reduce their labor supply during the week due to elevated pollution levels, we should not expect to see significant differences between the days of the week on which the time diary is recorded. This finding contrasts that in Connolly (2008) who finds that the effect of rain on time spent on work is higher during the beginning and end of the week.

We now examine if our results differ across different regions of the country. Since certain regions are, on average, more polluted than other regions, residents of more polluted regions may have adapted to higher average pollution concentrations that they experience. As we saw in Figure **??**, Indo-Gangetic plains are relatively more polluted than other parts of the country. We examine if residents of this region differentially change their time-use on outdoor activities on account of high pollution levels. We present results from estimating our main specifications by restricting the estimating to five distinct regions in Table 18. We find that in almost all the regions, high pollution levels are associated with reduced time on outdoor activities. We are, however, underpowered to detect differential effects across regions.

4.4 Mechanisms

We next examine if the effect of air pollution exposure on the time spent on activities that are performed outdoors differs by whether the district in which the respondent resides has a ground-based pollution monitor. As 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 information on air quality leads to respondents reducing their time on activities that are performed outdoors more. We obtained 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 to be residing in a district with an air pollution monitor if the 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 estimate the specifications in Equation (1) - (3) and present results in Table 19. Our point estimates do not suggest that the effect of air pollution exposure on time spent on activities that are performed outdoors is more pronounced for residents of the districts that have a ground-based air pollution monitor. We, however, exercise caution in interpreting this as better air quality information being inconsequential in affecting the time use patterns of the respondents as we are underpowered in detecting any marginal effect of air quality information through ground-based air pollution monitors. Not every district in India has ground-based air pollution monitors. Further, these monitors provide intermittent information about air quality due to frequent outages.

4.5 Non-linear Effects

We conclude this section by examining if the estimated effect of air pollution exposure on time spent on activities that are performed outdoors is non-linear. We estimate specifications in Equation (1) - (3). We modify these equations by replacing the continuous $PM_{2.5}$ concentration variable with an indicator for this concentration to be higher than 100 $\mu g/m^3$. We present results from estimating these specifications in Table 20. While our point estimates suggest a substantially larger effect of air pollution exposure on time spent on activities that are performed outdoors, the effect is only weakly statistically significant.

5 Discussion and Conclusion

We examine if and how air pollution exposure affects time spent on activities that are performed outdoors. We take time spent on activities that are performed outdoors as our measure of avoidance behavior due to air pollution exposure. We use nationally representative survey data on time-use from India. These data provide detailed information on time spent on various categories in 30-minute time intervals. We construct a measure of air pollution exposure using satellite reanalysis data on $PM_{2.5}$ concentrations. To uncover the causal effect of air pollution exposure on time-use patterns, we leverage changes in local wind directions in an IV setup. Our point estimates from the preferred IV specifications suggest that one standard deviation (sd) increase in $PM_{2.5}$ concentration reduces time spent on outdoor activities by 0.04 sd. This is equivalent to a decline of approximately seven minutes in time spent on activities that are performed outdoors, a 4.4% decline in time spent on activities that are performed outdoors over the sample mean. We find that our main effect of reduction in time spent outdoors is robust to multiple changes to the estimating sample. The baseline effect is not conflated by the non-random selection of households for interviews on less or more polluted days. Further, we depict that the main effect is due to contemporaneous exposure to elevated levels of air pollution and not its lag or lead.

Additionally, our effects are heterogeneous across subgroups and broad categories of activities. We find that the main effect of reduced time on activities that are performed outdoors is more pronounced for respondents who identify as male, residents of rural areas, and households who are relatively worse off in terms of socioeconomic status. We also find that almost all of the decline in time allocated on outdoor activities results from the decline in time spent on activities related to employment outdoors. Further, we find that this time saved from employment-related outdoor activities is reallocated to leusure-related indoor or unpaid care-related outdoor activities. Moreover, the elevated levels of air pollution might lead to more equitable intrahousehold distribution of activities related to unpaid care. Particularly, we find that on more polluted days, the share of male members' time spent on activities that are performed outdoors and are related to unpaid care increases. We observe that the main effect is declining monotonically with the education level of the respondent. We also show that the reduction in time spent on activities that are performed outdoors is driven by the employment of respondents in jobs that afford flexibility in the labor supply decisions. Finally, the effects are almost entirely driven by respondents employed in industries that are classified as high-risk due to their requirement to work outdoors.

Our work has several limitations. We are unable to observe how employers respond to the elevated levels of air pollution that lead to a decline in the labor supply, especially in industries where almost all of the work is performed outdoors. 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. Since we do not observe direct measures of wages, we are unable to obtain the precise monetary cost of the reduced labor supply due to exposure to elevated levels of air pollution. We leave it for the future work to help addressing some of these shortcomings.

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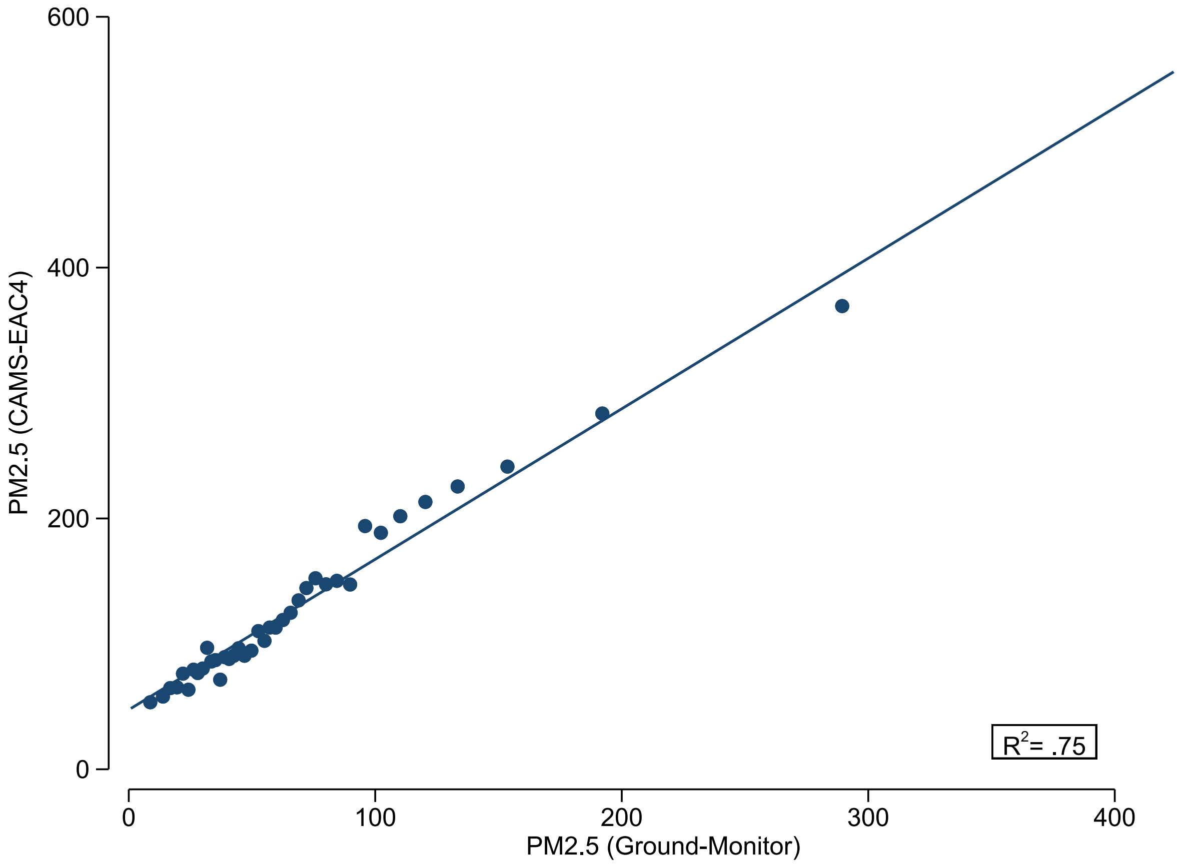
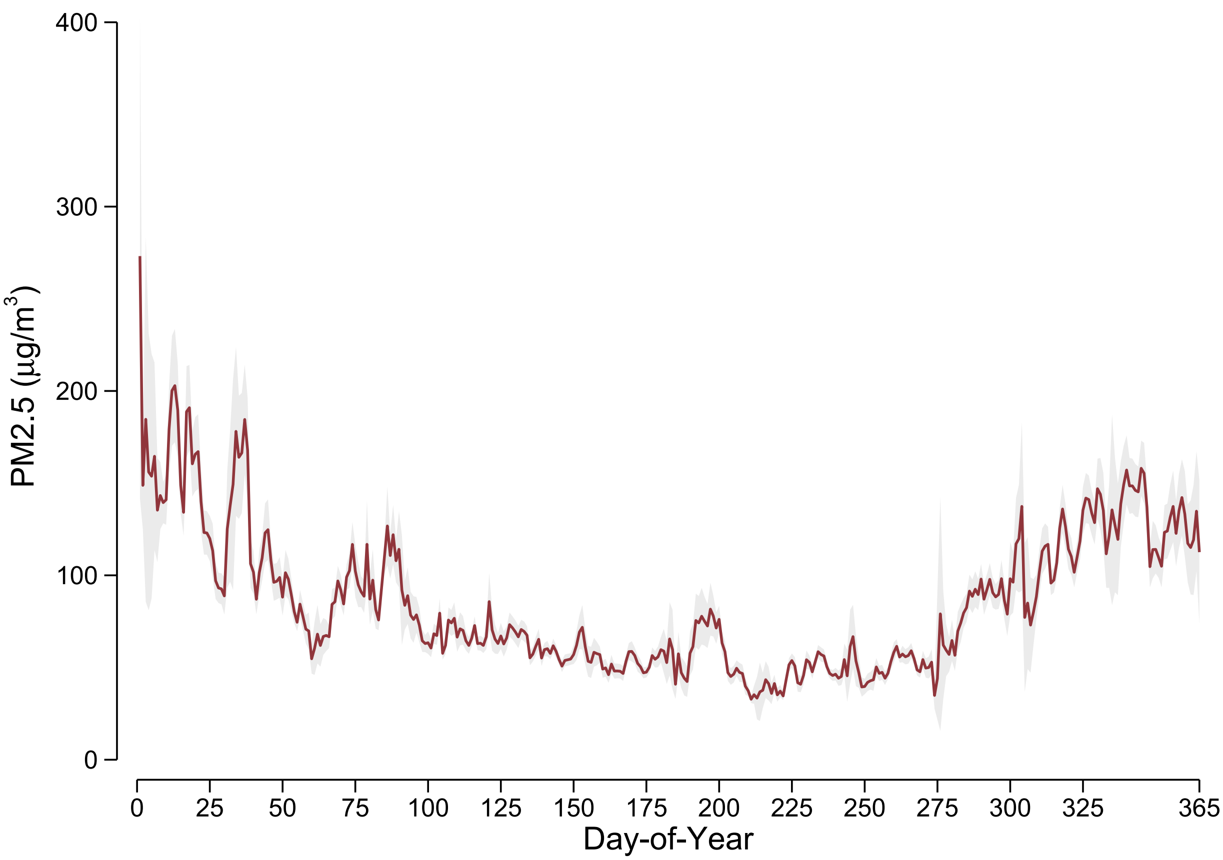
Figure 1: Correlation between Ground Monitor and CAMS-EAC4 Data



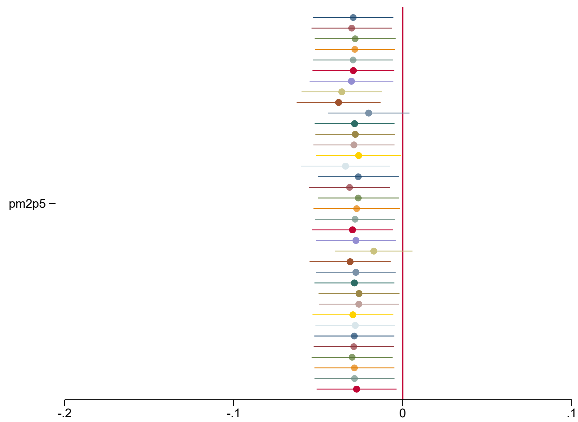
Note: Data for ground monitors $PM_{2.5}$ concentrations comes from the Central Pollution Control Board (CPCB), Ministry of Environment, Forest and Climate Change, Govt. of India Central Control Room for Air Quality Management. CAMS-EAC4 data is provided by the European Centre for Medium-Range Weather Forecasts (ECMWF). R^2 is from regressing CAMS-EAC4 $PM_{2.5}$ concentration levels on ground-monitor $PM_{2.5}$ concentration levels. 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.

Figure 2: Temporal Variation in $PM_{2.5}$ Concentration

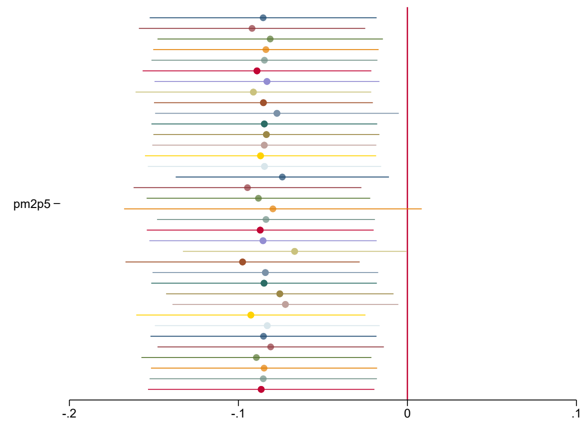


Note: Data on $PM_{2.5}$ concentration comes from CAMS-EAC4 satellite reanalysis data provided by the European Centre for Medium-Range Weather Forecasts (ECMWF). The mean $PM_{2.5}$ concentration across all districts for each day of the year, along with the 95% confidence interval, is plotted.

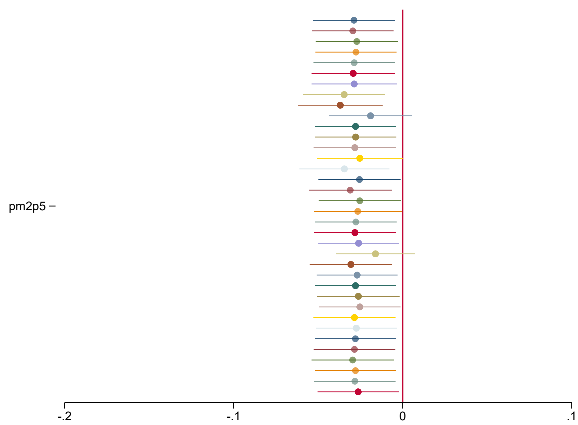
Figure 3: Robustness Check: Dropping one state at a time



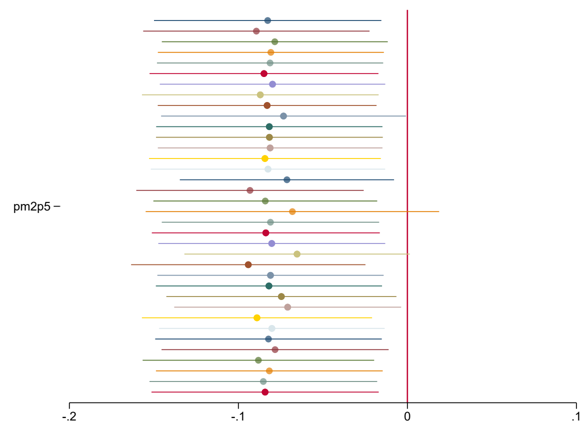
(a) OLS: Both Major and Minor Activity



(b) IV: Both Major and Minor Activity



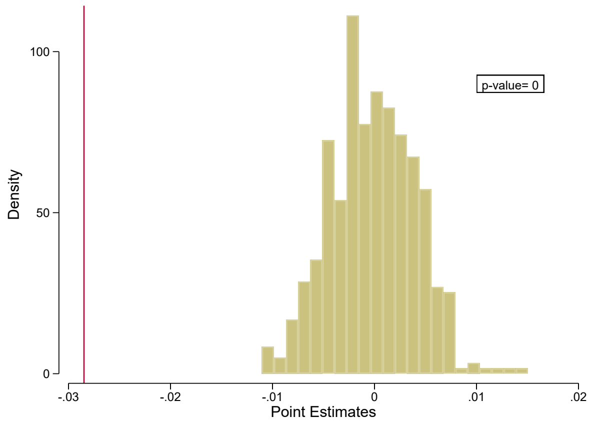
(c) OLS: Only Major Activity



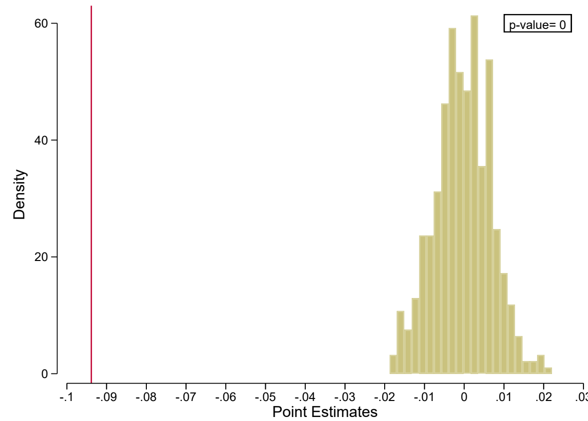
(d) IV: Only Major Activity

Note: Heteroskedasticity robust standard errors clustered by the district are used to construct the 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. We drop one state from the estimating sample for each specification. Each specification includes individual controls, household controls, weather controls, district, day-of-week, and day-of-year fixed-effects. Individual controls include gender, age, highest education level, and usual principal activity status of the respondent. Household controls include the number of members in the household, religion, social group, usual monthly consumption expenditure, and primary source of energy for cooking. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables in IV specifications are interactions of the district clusters and wind direction quadrant 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. Estimates on the $PM_{2.5}$ concentration variable are plotted.

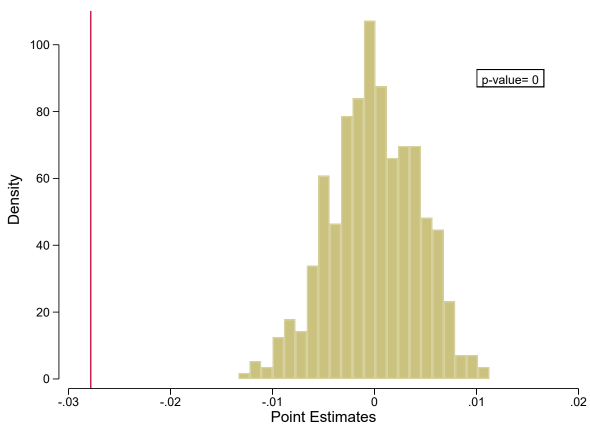
Figure 4: Placebo Check: Randomization Inference



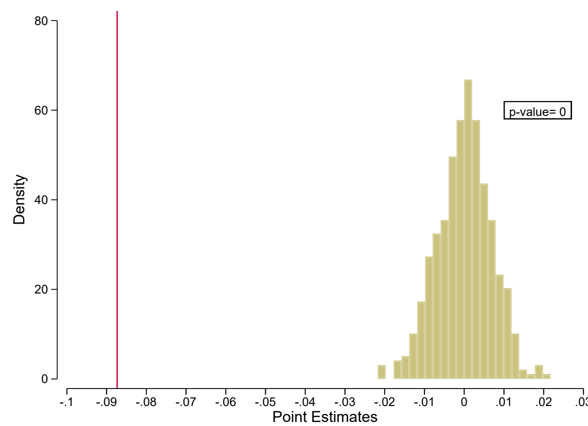
(a) OLS: Both Major and Minor Activity



(b) IV: Both Major and Minor Activity



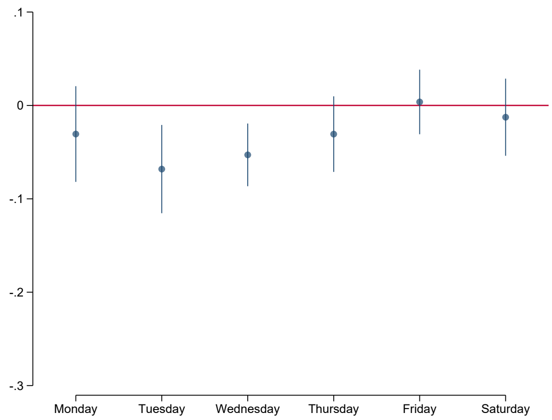
(c) OLS: Only Major Activity



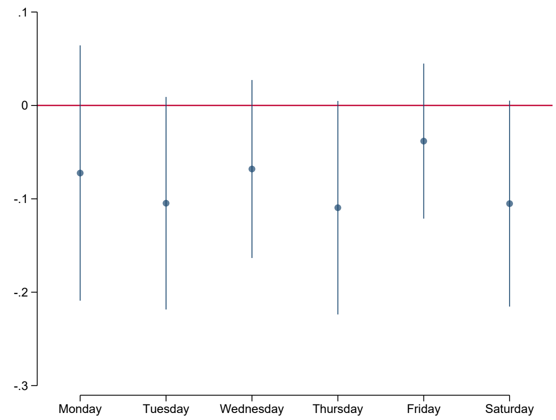
(d) IV: Only Major Activity

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 individual controls, household controls, weather controls, district, and day-of-year fixed-effects. Individual controls include gender, age, highest education level, and usual principal activity status of the respondent. Household controls include the number of members in the household, religion, social group, usual monthly consumption expenditure, and primary source of energy for cooking. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables in IV specifications are interactions of the district clusters and wind direction quadrant 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.

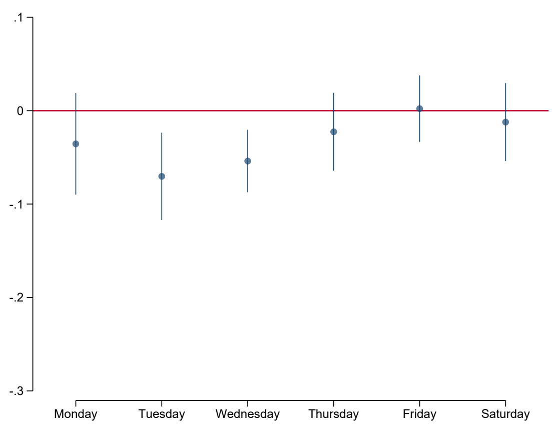
Figure 5: Heterogeneous Effects of Air Pollution on Time Spent on Activities that are Performed Outdoors: Day-of-Week



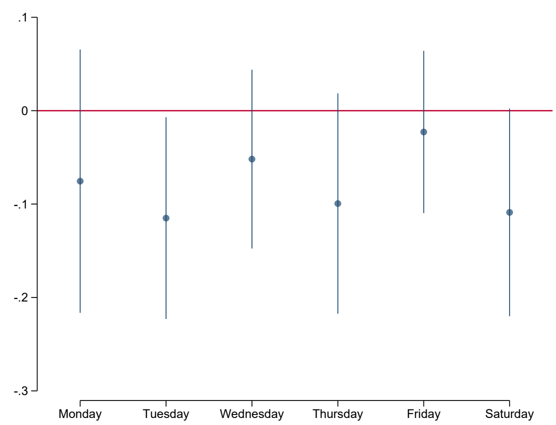
(a) OLS: Both Major and Minor Activity



(b) IV: Both Major and Minor Activity



(c) OLS: Only Major Activity



(d) IV: Only Major Activity

Note: Heteroskedasticity robust standard errors clustered by the district are used to construct the 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 individual controls, household controls, weather controls, district, and day-of-year fixed-effects. Individual controls include gender, age, highest education level, and usual principal activity status of the respondent. Household controls include the number of members in the household, religion, social group, usual monthly consumption expenditure, and primary source of energy for cooking. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables in IV specifications are interactions of the district clusters and wind direction quadrant 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. Estimates on the $PM_{2.5}$ concentration variable are plotted.

Table 1: 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 2: Summary Statistics

	N	Mean	SD	Min	Max
Individual Controls					
Sex					
male	314,038	0.497	0.500	0.00	1.00
female	314,038	0.503	0.500	0.00	1.00
transgender	314,038	0.000	0.000	0.00	0.00
Marital Status					
never married	314,038	0.189	0.391	0.00	1.00
currently married	314,038	0.759	0.428	0.00	1.00
widowed	314,038	0.047	0.211	0.00	1.00
divorced/separated	314,038	0.006	0.075	0.00	1.00
Highest Education Level					
not literate	314,038	0.236	0.425	0.00	1.00
literate: below primary	314,038	0.070	0.255	0.00	1.00
primary	314,038	0.119	0.324	0.00	1.00
upper primary/middle	314,038	0.160	0.366	0.00	1.00
secondary	314,038	0.144	0.351	0.00	1.00
higher secondary	314,038	0.120	0.325	0.00	1.00
diploma /certificate course (up to secondary)	314,038	0.009	0.096	0.00	1.00
diploma/certificate course (higher secondary)	314,038	0.011	0.105	0.00	1.00
diploma/certificate course(graduation and above)	314,038	0.009	0.095	0.00	1.00
graduate	314,038	0.092	0.289	0.00	1.00
post graduate and above	314,038	0.029	0.169	0.00	1.00
Usual Principal Activity Status					
Self-employed	314,038	0.248	0.432	0.00	1.00
Regular salaried/ wage employee	314,038	0.136	0.343	0.00	1.00
Casual wage labour	314,038	0.165	0.371	0.00	1.00
Unemployed	314,038	0.018	0.135	0.00	1.00
Attended educational institution	314,038	0.072	0.259	0.00	1.00
Attended domestic duties	314,038	0.337	0.473	0.00	1.00
Retired	314,038	0.013	0.113	0.00	1.00
Not able to work due to disability	314,038	0.006	0.077	0.00	1.00
Others	314,038	0.005	0.072	0.00	1.00
Household Controls					
Household Size	137,791	3.719	1.776	1.00	23.00
Usual Monthly Consumption Expenditure	137,789	9129.267	7405.690	6.00	301208.00
Religion					
Hinduism	137,791	0.821	0.384	0.00	1.00
Islam	137,791	0.123	0.329	0.00	1.00
Christianity	137,791	0.029	0.167	0.00	1.00
Sikhism	137,791	0.015	0.123	0.00	1.00
Jainism	137,791	0.002	0.047	0.00	1.00
Buddhism	137,791	0.005	0.073	0.00	1.00
Zoroastrianism	137,791	0.000	0.021	0.00	1.00
others	137,791	0.004	0.062	0.00	1.00
Social Group					
Scheduled Tribes (ST)	137,791	0.101	0.302	0.00	1.00
Scheduled Castes (SC)	137,791	0.194	0.395	0.00	1.00
Other Backward Classes (OBC)	137,791	0.424	0.494	0.00	1.00
Others	137,791	0.281	0.449	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 3: Time Spent on Indoor and Outdoor Activities

	$PM2.5 \leq 100\mu g/m^3$		$PM2.5 > 100\mu g/m^3$	
	Indoor Activities	Outdoor Activities	Indoor Activities	Outdoor Activities
Panel A: Both Major and Minor Activity				
Time (minutes)	1276.831	163.169	1297.933	142.067
	(185.681)	(185.681)	(178.833)	(178.833)
Panel B: Only Major Activity				
Time (minutes)	1272.126	167.874	1295.316	144.684
	(193.004)	(193.004)	(184.821)	(184.821)

Notes: Standard Deviations 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. 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.

Table 4: Effect of Air Pollution on Time Spent Outdoors – Main Effect

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) IV	(8) OLS	(9) IV
Panel A: Both Major and Minor Activity									
$PM2.5\ (\mu g/m^3)$	-0.131	0.009	-0.023	-0.020	-0.020	-0.030	-0.097	-0.028	-0.094
	(0.016)***	(0.012)	(0.013)*	(0.011)*	(0.011)*	(0.012)**	(0.033)***	(0.012)**	(0.034)***
Individual Controls				✓	✓	✓	✓	✓	✓
HH Controls					✓	✓	✓	✓	✓
Weather Controls						✓	✓	✓	✓
District FE		✓	✓	✓	✓	✓	✓	✓	✓
DoW FE			✓	✓	✓	✓	✓	✓	✓
Day-of-Year FE								✓	✓
Adj. R2	0.003	0.051	0.052	0.346	0.357	0.357	0.321	0.357	0.321
Dep. Var. Mean	157.875	157.875	157.875	157.875	157.875	157.875	157.875	157.875	157.875
Dep. Var. SD	184.214	184.214	184.214	184.214	184.214	184.214	184.214	184.214	184.214
Indep. Var. SD	73.661	73.661	73.661	73.661	73.661	73.661	73.661	73.661	73.661
KP F-Statistic							17.344		16.711
N	314,125	314,125	314,125	314,125	314,125	314,125	314,125	314,125	314,125
Panel B: Only Major Activity									
$PM2.5\ (\mu g/m^3)$	-0.145	0.010	-0.022	-0.020	-0.019	-0.029	-0.090	-0.028	-0.087
	(0.017)***	(0.012)	(0.013)*	(0.011)*	(0.011)*	(0.012)**	(0.033)***	(0.012)**	(0.034)***
Individual Controls				✓	✓	✓	✓	✓	✓
HH Controls					✓	✓	✓	✓	✓
Weather Controls						✓	✓	✓	✓
District FE		✓	✓	✓	✓	✓	✓	✓	✓
DoW FE			✓	✓	✓	✓	✓	✓	✓
Day-of-Year FE								✓	✓
Adj. R2	0.003	0.050	0.052	0.350	0.361	0.361	0.326	0.362	0.326
Dep. Var. Mean	162.057	162.057	162.057	162.057	162.057	162.057	162.057	162.057	162.057
Dep. Var. SD	191.248	191.248	191.248	191.248	191.248	191.248	191.248	191.248	191.248
Indep. Var. SD	73.661	73.661	73.661	73.661	73.661	73.661	73.661	73.661	73.661
KP F-Statistic							17.344		16.711
N	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. Activities classified as outdoor are discussed in the main text. The specification in column (4) includes individual controls, namely gender, age, highest education level, and usual principal activity status of the respondent. The specification in column (5) adds household controls, namely the number of members in the household, religion, social group, usual monthly consumption expenditure, and primary source of energy for cooking, to the specification in column (4). Specifications in column (6) to column (9) add weather controls to the specification in column (5). Weather controls contain precipitation, temperature, and wind speed. Instrumental variables in the specifications of column (7) and column (9) are interactions of the district clusters and wind direction quadrant 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 5: Effect of Air Pollution on Time Spent Outdoors: Robustness Checks

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV	(9) OLS	(10) IV	(11) OLS	(12) IV
	Baseline		Normal Day		Other Day		Drop Outliers		Full Sample		MERRA-2	
Panel A: Both Major and Minor Activity												
$PM2.5\,(\mu g/m^3)$	-0.028	-0.094	-0.029	-0.086	-0.002	0.005	-0.023	-0.073	-0.020	-0.073	-0.001	-0.149
	(0.012)**	(0.034)***	(0.012)**	(0.034)**	(0.028)	(0.078)	(0.010)**	(0.028)***	(0.010)**	(0.027)***	(0.028)	(0.094)
Adj. R2	0.357	0.321	0.385	0.347	0.167	0.075	0.337	0.295	0.373	0.347	0.357	0.321
Dep. Var. Mean	157.875	157.875	161.128	161.128	118.162	118.162	134.601	134.601	134.947	134.947	157.875	157.875
KP F-Statistic		16.711		16.638		12.472		16.464		17.079		25.522
N	314,125	314,125	290,331	290,331	23,784	23,784	299,140	299,140	442,607	442,607	314,125	314,125
Panel B: Only Major Activity												
$PM2.5\,(\mu g/m^3)$	-0.028	-0.087	-0.029	-0.078	0.012	-0.014	-0.024	-0.071	-0.021	-0.070	-0.001	-0.133
	(0.012)**	(0.034)***	(0.012)**	(0.034)**	(0.030)	(0.081)	(0.011)**	(0.029)**	(0.010)**	(0.027)***	(0.029)	(0.096)
Adj. R2	0.362	0.326	0.390	0.353	0.165	0.075	0.352	0.311	0.376	0.350	0.362	0.326
Dep. Var. Mean	162.057	162.057	165.262	165.262	122.924	122.924	143.439	143.439	138.449	138.449	162.057	162.057
KP F-Statistic		16.711		16.638		12.472		16.253		17.079		25.522
N	314,125	314,125	290,331	290,331	23,784	23,784	302,630	302,630	442,607	442,607	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 columns (9) and (10). 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 columns (3) and (4), the sample is restricted to days classified as "normal" according to the survey. In columns (5) and (6), the sample is restricted to days classified as "other" according to the survey. In columns (7) and (8), the sample is restricted to respondents who report time spent on outdoor activities below the 95th percentile of the sample. Columns (9) and (10) include all respondents who are above the age of six, irrespective of their reported gender. In columns (11) and (12), CAMS-EAC4 $PM2.5$ concentration measure is replaced with MERRA-2 $PM2.5$ concentration measure. Each specification in all columns includes individual controls, household controls, weather controls, district, day-of-week, and day-of-year fixed-effects. Individual controls include gender, age, highest education level, and usual principal activity status of the respondent. Household controls include the number of members in the household, religion, social group, usual monthly consumption expenditure, and primary source of energy for cooking. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables in IV specifications are interactions of the district clusters and wind direction quadrant 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 6: Effect of Air Pollution on Number of Interviews

	(1) OLS	(2) IV
Panel A: Both Major and Minor Activity		
$PM2.5\ (\mu g/m^3)$	-0.00057	-0.00140
	(0.00043)	(0.00121)
Weather Controls	✓	✓
District FE	✓	✓
DoW FE	✓	✓
Day-of-Year FE	✓	✓
Adj. R2	0.207	-0.008
Dep. Var. Mean	2.914	2.914
KP F-Statistic		20.740
N	47,298	47,298
Panel B: Only Major Activity		
$PM2.5\ (\mu g/m^3)$	-0.00057	-0.00140
	(0.00043)	(0.00121)
Weather Controls	✓	✓
District FE	✓	✓
DoW FE	✓	✓
Day-of-Year FE	✓	✓
Adj. R2	0.207	-0.008
Dep. Var. Mean	2.914	2.914
KP F-Statistic		20.740
N	47,298	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, day-of-week, 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 wind direction quadrant 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 7: Effect of Air Pollution on Time Spent Outdoors: Other Pollutants

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV	(9) OLS	(10) IV
	Baseline		Ozone		NO2		SO2		All Pollutants	
Panel A: Both Major and Minor Activity										
$PM2.5\,(\mu g/m^3)$	-0.029	-0.094							-0.028	-0.100
	(0.012)**	(0.034)***							(0.013)**	(0.041)**
$O_3\,(\mu g/m^2)$			-0.000	-0.000					-0.000	-0.000
			(0.000)	(0.000)					(0.000)	(0.000)
$NO_2\,(\mu g/m^2)$					-0.000	-0.002			0.000	-0.000
					(0.001)	(0.002)			(0.001)	(0.002)
$SO_2\,(\mu g/m^2)$							-0.000	-0.001	-0.000	0.000
							(0.000)	(0.001)	(0.000)	(0.001)
Adj. R2	0.357	0.321	0.357	0.321	0.357	0.321	0.357	0.321	0.358	0.320
Dep. Var. Mean	157.875	157.875	157.875	157.875	157.875	157.875	157.875	157.875	157.875	157.875
KP F-Statistic		16.662		26.882		18.131		26.668		21.941
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										
$PM2.5\,(\mu g/m^3)$	-0.028	-0.087							-0.026	-0.098
	(0.012)**	(0.034)***							(0.013)*	(0.042)**
$O_3\,(\mu g/m^2)$			-0.000	-0.000					-0.000	-0.000
			(0.000)	(0.000)					(0.000)	(0.000)
$NO_2\,(\mu g/m^2)$					-0.001	-0.002			-0.000	-0.000
					(0.001)	(0.002)			(0.001)	(0.002)
$SO_2\,(\mu g/m^2)$							-0.000	-0.001	-0.000	0.000
							(0.000)	(0.001)	(0.000)	(0.001)
Adj. R2	0.362	0.326	0.362	0.326	0.362	0.326	0.362	0.326	0.362	0.326
Dep. Var. Mean	162.057	162.057	162.057	162.057	162.057	162.057	162.057	162.057	162.057	162.057
KP F-Statistic		16.662		26.882		18.131		26.668		21.941
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 outdoor activities in minutes. Activities classified as outdoor are discussed in the main text. Each specification in all columns includes individual controls, household controls, weather controls, district, day-of-week, and day-of-year fixed-effects. Individual controls include gender, age, highest education level, and usual principal activity status of the respondent. Household controls include the number of members in the household, religion, social group, usual monthly consumption expenditure, and primary source of energy for cooking. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables in IV specifications are interactions of the district clusters and wind direction quadrant 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 8: Effect of Air Pollution on Time Spent Outdoors: Robustness to Alternate District Clusters

	(1) OLS	(2) IV	(3) IV	(4) IV	(5) IV
	Baseline		50 Clusters	60 Clusters	70 clusters
Panel A: Both Major and Minor Activity					
$PM2.5\ (\mu g/m^3)$	-0.029	-0.094	-0.073	-0.074	-0.074
	(0.012)**	(0.034)***	(0.029)**	(0.031)**	(0.030)**
Adj. R2	0.357	0.321	0.321	0.321	0.321
Dep. Var. Mean	157.875	157.875	157.875	157.875	157.875
KP F-Statistic		16.662	16.436	53.215	49.041
N	314,125	314,125	314,125	314,125	314,125
Panel B: Only Major Activity					
$PM2.5\ (\mu g/m^3)$	-0.028	-0.087	-0.069	-0.069	-0.075
	(0.012)**	(0.034)***	(0.029)**	(0.030)**	(0.030)**
Adj. R2	0.362	0.326	0.326	0.326	0.326
Dep. Var. Mean	162.057	162.057	162.057	162.057	162.057
KP F-Statistic		16.662	16.436	53.215	49.041
N	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. The column headings indicate the number of clusters that are used to classify districts. Each specification in all columns includes individual controls, household controls, weather controls, district, day-of-week, and day-of-year fixed-effects. Individual controls include gender, age, highest education level, and usual principal activity status of the respondent. Household controls include the number of members in the household, religion, social group, usual monthly consumption expenditure, and primary source of energy for cooking. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables in IV specifications are interactions of the district clusters and wind direction quadrant 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 9: Effect of Air Pollution on Time Spent Outdoors: Placebo Check

	(1) OLS	(2) IV	(3) OLS	(4) IV
	Baseline		Include Lag and Lead	
Panel A: Both Major and Minor Activity				
$PM2.5\,(\mu g/m^3)$	-0.028	-0.094	-0.007	-0.143
	(0.012)**	(0.034)***	(0.011)	(0.063)**
$PM2.5\,(\mu g/m^3)$ Lag			-0.006	0.006
			(0.011)	(0.063)
$PM2.5\,(\mu g/m^3)$ Lead			-0.024	0.053
			(0.010)**	(0.060)
Adj. R2	0.357	0.321	0.358	0.321
Dep. Var. Mean	157.875	157.875	157.875	157.875
KP F-Statistic		16.711		17.619
N	314,125	314,125	314,125	314,125
Panel B: Only Major Activity				
$PM2.5\,(\mu g/m^3)$	-0.028	-0.087	-0.010	-0.139
	(0.012)**	(0.034)***	(0.011)	(0.067)**
$PM2.5\,(\mu g/m^3)$ Lag			-0.006	-0.007
			(0.011)	(0.065)
$PM2.5\,(\mu g/m^3)$ Lead			-0.019	0.066
			(0.011)*	(0.062)
Adj. R2	0.362	0.326	0.362	0.326
Dep. Var. Mean	162.057	162.057	162.057	162.057
KP F-Statistic		16.711		17.619
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. Each specification in all columns includes individual controls, household controls, weather controls, district, day-of-week, and day-of-year fixed-effects. Individual controls include gender, age, highest education level, and usual principal activity status of the respondent. Household controls include the number of members in the household, religion, social group, usual monthly consumption expenditure, and primary source of energy for cooking. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables in IV specifications are interactions of the district clusters and wind direction quadrant 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 10: Effect of Air Pollution on Time Spent Outdoors: Heterogeneity

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV	(9) OLS	(10) IV	(11) OLS	(12) IV
	Male		Female		Rural		Urban		< Median MCE		> Median MCE	
Panel A: Both Major and Minor Activity												
$PM2.5\,(\mu g/m^3)$	-0.043	-0.115	-0.013	-0.076	-0.054	-0.145	0.005	-0.005	-0.049	-0.137	-0.011	-0.040
	(0.017)**	(0.050)**	(0.011)	(0.028)***	(0.020)***	(0.055)***	(0.012)	(0.025)	(0.019)***	(0.050)***	(0.013)	(0.032)
Adj. R2	0.256	0.192	0.347	0.261	0.391	0.355	0.234	0.205	0.375	0.339	0.329	0.287
Dep. Var. Mean	224.675	224.675	91.689	91.689	196.254	196.254	100.213	100.213	180.297	180.297	135.550	135.550
KP F-Statistic		17.103		16.296		13.051		12.651		15.299		11.764
N	156,338	156,338	157,787	157,787	188,598	188,598	125,527	125,527	156,723	156,723	157,398	157,398
Panel B: Only Major Activity												
$PM2.5\,(\mu g/m^3)$	-0.041	-0.114	-0.013	-0.063	-0.049	-0.138	0.004	-0.001	-0.052	-0.137	-0.009	-0.030
	(0.017)**	(0.051)**	(0.011)	(0.028)**	(0.020)**	(0.055)**	(0.012)	(0.025)	(0.020)**	(0.050)***	(0.013)	(0.032)
Adj. R2	0.256	0.193	0.346	0.260	0.398	0.364	0.235	0.206	0.381	0.346	0.332	0.290
Dep. Var. Mean	232.918	232.918	91.846	91.846	201.792	201.792	102.357	102.357	184.785	184.785	139.426	139.426
KP F-Statistic		17.103		16.296		13.051		12.651		15.299		11.764
N	156,338	156,338	157,787	157,787	188,598	188,598	125,527	125,527	156,723	156,723	157,398	157,398

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 individual controls, household controls, weather controls, district, day-of-week, and day-of-year fixed-effects. Individual controls include gender, age, highest education level, and usual principal activity status of the respondent. Household controls include the number of members in the household, religion, social group, usual monthly consumption expenditure, and primary source of energy for cooking. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables in IV specifications are interactions of the district clusters and wind direction quadrant 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 11: Effect of Air Pollution on Time Spent Outdoors – Effect by Major Activity Classification

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV	(9) OLS	(10) IV	(11) OLS	(12) IV	(13) OLS	(14) IV	(15) OLS	(16) IV
	Indoor								Outdoor							
	MD 1		MD 2		MD 3,4,5		MD 6,7,8,9		MD 1		MD 2		MD 3,4,5		MD 6,7,8,9	
Panel A: Both Major and Minor Activity																
$PM2.5\,(\mu g/m^3)$	0.019	-0.024	0.001	0.002	0.009	0.022	-0.001	0.093	-0.046	-0.099	0.012	-0.004	0.007	0.017	-0.001	-0.008
	(0.011)*	(0.029)	(0.002)	(0.004)	(0.010)	(0.024)	(0.014)	(0.037)**	(0.012)***	(0.033)***	(0.007)	(0.019)	(0.003)**	(0.007)**	(0.002)	(0.006)
Adj. R2	0.420	0.384	0.021	0.001	0.685	0.679	0.395	0.371	0.351	0.309	0.195	0.090	0.047	0.016	0.164	0.135
Dep. Var. Mean	114.984	114.984	1.624	1.624	181.731	181.731	983.786	983.786	99.663	99.663	28.273	28.273	16.586	16.586	13.353	13.353
KP F-Statistic		16.711		16.711		16.711		16.711		16.711		16.711		16.711		16.711
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	314,125	314,125	314,125	314,125
Panel B: Only Major Activity																
$PM2.5\,(\mu g/m^3)$	0.018	-0.010	0.001	0.002	0.007	0.022	0.002	0.073	-0.046	-0.092	0.012	-0.003	0.008	0.018	-0.002	-0.010
	(0.012)	(0.029)	(0.002)	(0.004)	(0.011)	(0.025)	(0.014)	(0.033)**	(0.012)***	(0.033)***	(0.008)	(0.020)	(0.003)**	(0.008)**	(0.002)	(0.007)
Adj. R2	0.426	0.391	0.022	0.001	0.680	0.673	0.402	0.380	0.353	0.311	0.197	0.090	0.038	0.009	0.154	0.126
Dep. Var. Mean	121.250	121.250	1.765	1.765	191.967	191.967	962.962	962.962	103.226	103.226	29.386	29.386	15.559	15.559	13.886	13.886
KP F-Statistic		16.711		16.711		16.711		16.711		16.711		16.711		16.711		16.711
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	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 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 individual controls, household controls, weather controls, district, day-of-week, and day-of-year fixed-effects. Individual controls include gender, age, highest education level, and usual principal activity status of the respondent. Household controls include the number of members in the household, religion, social group, usual monthly consumption expenditure, and primary source of energy for cooking. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables in IV specifications are interactions of the district clusters and wind direction quadrant 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 12: Effect of Air Pollution on Time Spent Outdoors – Effect by Major Activity Classification and Male Share

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	Indoor								Outdoor							
	MD 1		MD 2		MD 3,4,5		MD 6,7,8,9		MD 1		MD 2		MD 3,4,5		MD 6,7,8,9	
Panel A: Both Major and Minor Activity																
$PM2.5\,(\mu g/m^3)$	0.004	0.010	0.000	-0.003	-0.000	-0.000	0.000	0.004	-0.004	-0.006	-0.002	-0.008	0.011	0.021	-0.007	-0.022
	(0.005)	(0.014)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)	(0.003)	(0.005)	(0.012)	(0.003)	(0.009)	(0.004)**	(0.011)*	(0.004)*	(0.013)*
Adj. R2	0.127	0.041	0.039	-0.002	0.055	0.001	0.019	0.002	0.074	0.003	0.145	0.023	0.094	-0.003	0.083	0.009
Dep. Var. Mean	48.825	48.825	0.857	0.857	6.820	6.820	51.076	51.076	68.164	68.164	14.387	14.387	18.103	18.103	22.997	22.997
KP F-Statistic		16.359		16.359		16.359		16.359		16.359		16.359		16.359		16.359
N	106,579	106,579	106,579	106,579	106,579	106,579	106,579	106,579	106,579	106,579	106,579	106,579	106,579	106,579	106,579	106,579
Panel B: Only Major Activity																
$PM2.5\,(\mu g/m^3)$	0.004	0.013	0.000	-0.004	-0.000	0.000	0.000	0.003	-0.004	-0.003	-0.001	-0.009	0.010	0.015	-0.008	-0.026
	(0.005)	(0.014)	(0.001)	(0.002)*	(0.001)	(0.003)	(0.001)	(0.003)	(0.005)	(0.012)	(0.003)	(0.009)	(0.004)**	(0.011)	(0.004)*	(0.013)**
Adj. R2	0.128	0.042	0.033	-0.002	0.055	0.000	0.019	0.003	0.074	0.002	0.144	0.023	0.090	-0.003	0.079	0.009
Dep. Var. Mean	48.504	48.504	0.764	0.764	6.611	6.611	51.158	51.158	67.647	67.647	14.166	14.166	17.811	17.811	21.992	21.992
KP F-Statistic		16.359		16.359		16.359		16.359		16.359		16.359		16.359		16.359
N	106,579	106,579	106,579	106,579	106,579	106,579	106,579	106,579	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 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 ratio of time spent on outdoor activities in minutes by male to female members of the households. 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 individual controls, household controls, weather controls, district, day-of-week, and day-of-year fixed-effects. Individual controls include gender, age, highest education level, and usual principal activity status of the respondent. Household controls include the number of members in the household, religion, social group, usual monthly consumption expenditure, and primary source of energy for cooking. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables in IV specifications are interactions of the district clusters and wind direction quadrant 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 13: Effect of Air Pollution on Time Spent Outdoors: Heterogeneity by Single or Muti Member Household

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
	Baseline		Multi member HH		Single member HH	
Panel A: Both Major and Minor Activity						
$PM2.5\,(\mu g/m^3)$	-0.028	-0.094	-0.027	-0.095	-0.082	-0.194
	(0.012)**	(0.034)***	(0.012)**	(0.034)***	(0.042)**	(0.077)**
Adj. R2	0.357	0.321	0.360	0.323	0.302	0.185
Dep. Var. Mean	157.875	157.875	158.560	158.560	133.115	133.115
KP F-Statistic		16.711		16.654		8.020
N	314,125	314,125	305,669	305,669	8,456	8,456
Panel B: Only Major Activity						
$PM2.5\,(\mu g/m^3)$	-0.028	-0.087	-0.027	-0.089	-0.083	-0.193
	(0.012)**	(0.034)***	(0.012)**	(0.034)***	(0.044)*	(0.072)***
Adj. R2	0.362	0.326	0.365	0.329	0.300	0.183
Dep. Var. Mean	162.057	162.057	162.782	162.782	135.827	135.827
KP F-Statistic		16.711		16.654		8.020
N	314,125	314,125	305,669	305,669	8,456	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 columns (3) and (4), the sample is restricted to multiple-member households. In columns (5) and (6), the sample is restricted to single-member households. Each specification in all columns includes individual controls, household controls, weather controls, district, day-of-week, and day-of-year fixed-effects. Individual controls include gender, age, highest education level, and usual principal activity status of the respondent. Household controls include the number of members in the household, religion, social group, usual monthly consumption expenditure, and primary source of energy for cooking. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables in IV specifications are interactions of the district clusters and wind direction quadrant 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 14: Effect of Air Pollution on Time Spent Outdoors: Heterogeneity by Age

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV
	Age $\leq$ 22		23 $\leq$ Age $\leq$ 45		46 $\leq$ Age $\leq$ 60		Age $>$ 60	
Panel A: Both Major and Minor Activity								
$PM2.5\left(\mu g/m^3\right)$	-0.020	-0.013	-0.025	-0.097	-0.035	-0.112	0.043	0.022
	(0.008)**	(0.024)	(0.013)**	(0.038)**	(0.020)*	(0.045)**	(0.018)**	(0.039)
Adj. R2	0.319	0.295	0.357	0.318	0.356	0.304	0.391	0.352
Dep. Var. Mean	76.818	76.818	161.104	161.104	177.763	177.763	119.587	119.587
KP F-Statistic		20.230		16.404		13.690		12.852
N	131,893	131,893	192,952	192,952	76,137	76,137	41,498	41,498
Panel B: Only Major Activity								
$PM2.5\left(\mu g/m^3\right)$	-0.020	-0.018	-0.025	-0.093	-0.036	-0.101	0.038	0.018
	(0.008)**	(0.024)	(0.013)*	(0.039)**	(0.020)*	(0.046)**	(0.018)**	(0.041)
Adj. R2	0.319	0.295	0.362	0.324	0.360	0.309	0.389	0.351
Dep. Var. Mean	78.487	78.487	165.236	165.236	182.800	182.800	123.169	123.169
KP F-Statistic		20.230		16.404		13.690		12.852
N	131,893	131,893	192,952	192,952	76,137	76,137	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 sample is restricted to respondents 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. Age restrictions for the sample are mentioned in the column header. Each specification in all columns includes individual controls, household controls, weather controls, district, day-of-week, and day-of-year fixed-effects. Individual controls include gender, age, highest education level, and usual principal activity status of the respondent. Household controls include the number of members in the household, religion, social group, usual monthly consumption expenditure, and primary source of energy for cooking. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables in IV specifications are interactions of the district clusters and wind direction quadrant 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 15: Effect of Air Pollution on Time Spent Outdoors: Heterogeneity by Education Level

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV
	Not Literate		Up to Primary School		Above Primary School		College	
Panel A: Both Major and Minor Activity								
$PM2.5\ (\mu g/m^3)$	-0.073	-0.186	-0.065	-0.144	-0.010	-0.081	0.016	0.025
	(0.027)***	(0.063)***	(0.024)***	(0.063)**	(0.015)	(0.040)**	(0.012)	(0.032)
Adj. R2	0.393	0.335	0.375	0.327	0.331	0.294	0.219	0.178
Dep. Var. Mean	193.294	193.294	191.915	191.915	161.929	161.929	101.583	101.583
KP F-Statistic		14.839		14.409		12.544		13.763
N	63,654	63,654	52,363	52,363	111,307	111,307	41,765	41,765
Panel B: Only Major Activity								
$PM2.5\ (\mu g/m^3)$	-0.079	-0.180	-0.061	-0.129	-0.009	-0.075	0.017	0.013
	(0.027)***	(0.063)***	(0.025)**	(0.064)**	(0.015)	(0.041)*	(0.012)	(0.033)
Adj. R2	0.400	0.344	0.382	0.336	0.337	0.300	0.217	0.177
Dep. Var. Mean	197.504	197.504	197.252	197.252	166.492	166.492	104.584	104.584
KP F-Statistic		14.839		14.409		12.544		13.763
N	63,654	63,654	52,363	52,363	111,307	111,307	41,765	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 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 individual controls, household controls, weather controls, district, day-of-week, and day-of-year fixed-effects. Individual controls include gender, age, and usual principal activity status of the respondent. Household controls include the number of members in the household, religion, social group, usual monthly consumption expenditure, and primary source of energy for cooking. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables in IV specifications are interactions of the district clusters and wind direction quadrant 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 16: Effect of Air Pollution on Time Spent Outdoors: Heterogeneity by Usual Principal Activity Status

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV
	Self-Employed		Regular Wage/Salaried Employee		Casual Labor		Unemployed or Not in Labor Force	
Panel A: Both Major and Minor Activity								
$PM2.5\left(\mu g/m^3\right)$	-0.026	-0.165	-0.011	-0.049	-0.175	-0.359	0.008	0.003
	(0.022)	(0.070)**	(0.018)	(0.043)	(0.048)***	(0.118)***	(0.009)	(0.021)
Adj. R2	0.174	0.088	0.095	0.032	0.164	0.021	0.138	0.071
Dep. Var. Mean	256.753	256.753	127.099	127.099	305.426	305.426	64.081	64.081
KP F-Statistic		16.806		17.032		12.759		15.930
N	79,556	79,556	45,996	45,996	46,557	46,557	142,016	142,016
Panel B: Only Major Activity								
$PM2.5\left(\mu g/m^3\right)$	-0.022	-0.152	-0.007	-0.048	-0.183	-0.359	0.008	0.010
	(0.022)	(0.069)**	(0.019)	(0.045)	(0.049)***	(0.116)***	(0.010)	(0.022)
Adj. R2	0.175	0.090	0.095	0.032	0.164	0.024	0.138	0.071
Dep. Var. Mean	265.540	265.540	131.204	131.204	316.006	316.006	63.610	63.610
KP F-Statistic		16.806		17.032		12.759		15.930
N	79,556	79,556	45,996	45,996	46,557	46,557	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 individual controls, household controls, weather controls, district, day-of-week, and day-of-year fixed-effects. Individual controls include gender and age. Household controls include the number of members in the household, religion, social group, usual monthly consumption expenditure, and primary source of energy for cooking. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables in IV specifications are interactions of the district clusters and wind direction quadrant 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 17: Effect of Air Pollution on Time Spent Outdoors: Heterogeneity by Industry Risk

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
	Baseline		Low-risk		High-risk	
Panel A: Both Major and Minor Activity						
$PM2.5\ (\mu g/m^3)$	-0.028	-0.094	0.005	0.012	-0.071	-0.244
	(0.012)**	(0.034)***	(0.013)	(0.034)	(0.026)***	(0.075)***
Adj. R2	0.357	0.321	0.066	0.024	0.185	0.092
Dep. Var. Mean	157.875	157.875	103.071	103.071	295.623	295.623
KP F-Statistic		16.711		14.324		14.204
N	314,125	314,125	53,946	53,946	118,163	118,163
Panel B: Only Major Activity						
$PM2.5\ (\mu g/m^3)$	-0.028	-0.087	0.008	0.021	-0.068	-0.234
	(0.012)**	(0.034)***	(0.014)	(0.037)	(0.027)**	(0.076)***
Adj. R2	0.362	0.326	0.068	0.025	0.186	0.095
Dep. Var. Mean	162.057	162.057	105.850	105.850	306.037	306.037
KP F-Statistic		16.711		14.324		14.204
N	314,125	314,125	53,946	53,946	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 the first two 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 the last four columns, the sample is restricted to respondents between the ages of 18 and 60, those who report their gender to be either male or female, and those who report being employed as their usual principal activity status. In columns (3) and (4), the sample is restricted to industries that are classified as low-risk. In columns (5) and (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 individual controls, household controls, weather controls, district, day-of-week, and day-of-year fixed-effects. Individual controls include gender, age, highest education level, and usual principal activity status of the respondent. Household controls include the number of members in the household, religion, social group, usual monthly consumption expenditure, and primary source of energy for cooking. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables in IV specifications are interactions of the district clusters and wind direction quadrant 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 18: Effect of Air Pollution on Time Spent Outdoors: Heterogeneity by Region

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV	(9) OLS	(10) IV
	North		West		South		East		Northeast	
Panel A: Both Major and Minor Activity										
$PM2.5\,(\mu g/m^3)$	0.010	-0.071	0.013	-0.049	0.060	0.426	-0.017	-0.022	-0.036	-0.219
	(0.027)	(0.085)	(0.075)	(0.222)	(0.072)	(0.385)	(0.036)	(0.071)	(0.019)*	(0.115)*
Adj. R2	0.312	0.268	0.384	0.310	0.349	0.313	0.439	0.418	0.360	0.324
Dep. Var. Mean	147.752	147.752	169.898	169.898	165.810	165.810	155.647	155.647	163.883	163.883
KP F-Statistic		12.370		20.828		46.615		29.979		3.181
N	111,257	111,257	46,141	46,141	61,641	61,641	59,348	59,348	35,738	35,738
Panel B: Only Major Activity										
$PM2.5\,(\mu g/m^3)$	0.004	-0.077	0.025	-0.038	0.047	0.486	-0.028	-0.056	-0.038	-0.201
	(0.028)	(0.086)	(0.070)	(0.213)	(0.078)	(0.425)	(0.035)	(0.073)	(0.021)*	(0.112)*
Adj. R2	0.315	0.272	0.391	0.319	0.356	0.320	0.442	0.421	0.363	0.330
Dep. Var. Mean	150.914	150.914	177.601	177.601	172.206	172.206	156.219	156.219	168.866	168.866
KP F-Statistic		12.370		20.828		46.615		29.979		3.181
N	111,257	111,257	46,141	46,141	61,641	61,641	59,348	59,348	35,738	35,738

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 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 individual controls, household controls, weather controls, district, day-of-week, and day-of-year fixed-effects. Individual controls include gender, age, and usual principal activity status of the respondent. Household controls include the number of members in the household, religion, social group, usual monthly consumption expenditure, and primary source of energy for cooking. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables in IV specifications are interactions of the district clusters and wind direction quadrant 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 19: Effect of Air Pollution on Time Spent Outdoors: Access to Air Quality Information

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
	Baseline		No Monitor		Has Monitor	
Panel A: Both Major and Minor Activity						
$PM2.5\ (\mu g/m^3)$	-0.028	-0.094	-0.038	-0.108	-0.002	-0.038
	(0.012)**	(0.034)***	(0.014)***	(0.038)***	(0.032)	(0.056)
Adj. R2	0.357	0.321	0.363	0.330	0.290	0.236
Dep. Var. Mean	157.875	157.875	162.447	162.447	121.589	121.589
KP F-Statistic		16.711		15.305		397.611
N	314,125	314,125	278,979	278,979	35,146	35,146
Panel B: Only Major Activity						
$PM2.5\ (\mu g/m^3)$	-0.028	-0.087	-0.036	-0.099	-0.009	-0.055
	(0.012)**	(0.034)***	(0.014)**	(0.038)***	(0.031)	(0.056)
Adj. R2	0.362	0.326	0.368	0.336	0.289	0.238
Dep. Var. Mean	162.057	162.057	166.801	166.801	124.398	124.398
KP F-Statistic		16.711		15.305		397.611
N	314,125	314,125	278,979	278,979	35,146	35,146

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 columns (3) and (4), the sample is restricted to districts that do not have an operating ground-based pollution monitor that measures $PM2.5$ concentration. In columns (5) and (6), the sample is restricted to districts that have an operating ground-based pollution monitor that measures $PM2.5$ concentration. Each specification in all columns includes individual controls, household controls, weather controls, district, day-of-week, and day-of-year fixed-effects. Individual controls include gender, age, highest education level, and usual principal activity status of the respondent. Household controls include the number of members in the household, religion, social group, usual monthly consumption expenditure, and primary source of energy for cooking. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables in IV specifications are interactions of the district clusters and wind direction quadrant 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 20: Effect of Air Pollution on Time Spent Outdoors: Non-Linear Effects

	(1) OLS	(2) IV	(3) OLS	(4) IV
	Baseline		High PM2.5	
Panel A: Both Major and Minor Activity				
$PM2.5\left(\mu g/m^3\right)$	-0.028	-0.094		
	(0.012)**	(0.034)***		
$PM2.5\left(\mu g/m^3\right) > 100$=1			-2.709	-11.565
			(2.109)	(6.291)*
Adj. R2	0.357	0.321	0.357	0.321
Dep. Var. Mean	157.875	157.875	157.875	157.875
KP F-Statistic		16.711		24.767
N	314,125	314,125	314,125	314,125
Panel B: Only Major Activity				
$PM2.5\left(\mu g/m^3\right)$	-0.028	-0.087		
	(0.012)**	(0.034)***		
$PM2.5\left(\mu g/m^3\right) > 100$=1			-2.198	-9.790
			(2.120)	(6.376)
Adj. R2	0.362	0.326	0.362	0.326
Dep. Var. Mean	162.057	162.057	162.057	162.057
KP F-Statistic		16.711		24.767
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. In columns (3) and (4), the continuous $PM2.5$ measure is replaced with an indicator variable for $PM2.5$ concentration to be greater than $100\mu g/m^3$. Each specification in all columns includes individual controls, household controls, weather controls, district, day-of-week, and day-of-year fixed-effects. Individual controls include gender, age, highest education level, and usual principal activity status of the respondent. Household controls include the number of members in the household, religion, social group, usual monthly consumption expenditure, and primary source of energy for cooking. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables in IV specifications are interactions of the district clusters and wind direction quadrant 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.

Appendices

Appendix A Figures and Tables

Table A1: Effect of Air Pollution on Time Spent Outdoors: Other Pollutants

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
	Baseline		PM1		PM10	
Panel A: Both Major and Minor Activity						
$PM2.5\,(\mu g/m^3)$	-0.029	-0.094				
	(0.012)**	(0.034)***				
$PM1\,(\mu g/m^3)$			-0.038	-0.115		
			(0.014)***	(0.041)***		
$PM10\,(\mu g/m^3)$					-0.020	-0.063
					(0.009)**	(0.024)***
Adj. R2	0.357	0.321	0.358	0.321	0.357	0.321
Dep. Var. Mean	157.875	157.875	157.875	157.875	157.875	157.875
KP F-Statistic		16.662		16.629		15.929
N	314,125	314,125	314,125	314,125	314,125	314,125
Panel B: Only Major Activity						
$PM2.5\,(\mu g/m^3)$	-0.028	-0.087				
	(0.012)**	(0.034)***				
$PM1\,(\mu g/m^3)$			-0.036	-0.106		
			(0.014)**	(0.040)***		
$PM10\,(\mu g/m^3)$					-0.019	-0.059
					(0.009)**	(0.024)**
Adj. R2	0.362	0.326	0.362	0.326	0.362	0.326
Dep. Var. Mean	162.057	162.057	162.057	162.057	162.057	162.057
KP F-Statistic		16.662		16.629		15.929
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 minutes. Activities classified as outdoor are discussed in the main text. The column header shows the pollutant. Each specification in all columns includes individual controls, household controls, weather controls, district, day-of-week, and day-of-year fixed-effects. Individual controls include gender, age, highest education level, and usual principal activity status of the respondent. Household controls include the number of members in the household, religion, social group, usual monthly consumption expenditure, and primary source of energy for cooking. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables in IV specifications are interactions of the district clusters and wind direction quadrant 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 A2: Effect of Air Pollution on Time Spent Outdoors – Effect by Major Activity Classification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	Indoor								Outdoor							
	MD 1		MD 2		MD 3,4,5		MD 6,7,8,9		MD 1		MD 2		MD 3,4,5		MD 6,7,8,9	
Panel A: Both Major and Minor Activity																
$PM2.5\,(\mu g/m^3)$	0.016	-0.025	0.001	0.001	0.009	0.028	-0.005	0.069	-0.035	-0.081	0.012	0.005	0.006	0.017	-0.003	-0.013
	(0.009)*	(0.022)	(0.001)	(0.003)	(0.009)	(0.021)	(0.011)	(0.032)**	(0.009)***	(0.026)***	(0.006)*	(0.016)	(0.002)**	(0.006)***	(0.003)	(0.007)**
Adj. R2	0.442	0.415	0.019	0.002	0.647	0.643	0.609	0.601	0.374	0.344	0.186	0.105	0.062	0.036	0.207	0.181
Dep. Var. Mean	86.505	86.505	1.340	1.340	144.376	144.376	1072.826	1072.826	77.208	77.208	23.900	23.900	13.781	13.781	20.065	20.065
KP F-Statistic		17.071		17.071		17.071		17.071		17.071		17.071		17.071		17.071
N	442,480	442,480	442,480	442,480	442,480	442,480	442,480	442,480	442,480	442,480	442,480	442,480	442,480	442,480	442,480	442,480
Panel B: Only Major Activity																
$PM2.5\,(\mu g/m^3)$	0.014	-0.013	0.001	0.001	0.007	0.026	-0.002	0.056	-0.035	-0.076	0.012	0.006	0.006	0.017	-0.003	-0.017
	(0.009)	(0.022)	(0.002)	(0.004)	(0.009)	(0.021)	(0.011)	(0.029)*	(0.009)***	(0.026)***	(0.006)*	(0.016)	(0.002)**	(0.006)***	(0.003)	(0.008)**
Adj. R2	0.448	0.422	0.020	0.003	0.642	0.637	0.617	0.609	0.376	0.346	0.187	0.105	0.050	0.025	0.191	0.166
Dep. Var. Mean	91.228	91.228	1.454	1.454	152.513	152.513	1056.349	1056.349	79.946	79.946	24.827	24.827	12.992	12.992	20.690	20.690
KP F-Statistic		17.071		17.071		17.071		17.071		17.071		17.071		17.071		17.071
N	442,480	442,480	442,480	442,480	442,480	442,480	442,480	442,480	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 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 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 individual controls, household controls, weather controls, district, day-of-week, and day-of-year fixed-effects. Individual controls include gender, age, highest education level, and usual principal activity status of the respondent. Household controls include the number of members in the household, religion, social group, usual monthly consumption expenditure, and primary source of energy for cooking. Weather controls contain precipitation, temperature, and wind speed. Instrumental variables in IV specifications are interactions of the district clusters and wind direction quadrant 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.