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ABSTRACT

Air Pollution and Time Use: Evidence from India*

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, consumption expenditure, 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 Classification: D13, J22, O13, 017, Q53, Q56

Keywords: air pollution, time-use, labor supply, intrahousehold bargaining, avoidance behavior, India

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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 how the exposed individuals respond to the elevated levels of air pollution. If these responses take the form of changes in routine behavior, then substantial costs might not be quantified. Further, these changes might also affect quotidian interactions. For instance, more time indoors might affect the intrahousehold allocation of tasks between different household members. To the extent that these changes take the form of labor market adjustment, the preexisting distortions in these markets may get amplified. If there are differential responses to the increased air pollution across individuals with different socioeconomic statuses, existing disparities in the negative impact of air pollution among these groups might be exacerbated.

The effect of air pollution exposure is, in large part, determined by the choices individuals make. Such choices available to an individual may be driven by their knowledge, beliefs, or preferences (Burke et al., 2022). Without policies limiting exposure, people are compelled to avoid pollution by protecting themselves from its hazardous levels. Thus, Avoidance behavior refers to the actions individuals privately undertake to change their exposure levels. As a result, it is vital to underline that factors like socioeconomic circumstances, information provision, and flexibility might drive the ability to undertake such actions. The lack of widespread air filtration technologies in many contexts suggests that avoidance behavior usually takes the form of time spent outdoors and indoors.

The existing works examining the effect of air pollution exposure on avoidance behavior are almost exclusively based in the United States, and the findings from these studies are unlikely to be extrapolated to developing country settings for multiple reasons. First, the information on air pollution is only sparsely available in developing countries. Therefore, the residents of these countries do not have enough information about their exposure and may not react effectively to the high levels of pollution. Second, even if the information on air quality is readily available, prevailing socioeconomic conditions may drive a wedge between developed and developing state residents' responses to its deterioration. 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 examine if and how the 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, we estimate the lower bounds of the true effect. Furthermore, due to high costs often associated with reducing time spent outdoors in developing countries, where many industries consist of occupations that are almost exclusively performed outdoors, time reallocation 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 account for them properly leads to underestimating 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.

Using data from the India Time Use Survey (ITUS), a large nationally representative dataset that encompasses information about time spent on daily 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 and above, performed in each 30-minute interval between 4 A.M. the day before the survey to 4 A.M. the survey day (time slots hereinafter). ITUS uses activity classification from the 2016 International Classification of Activities for Time Use Statistics (ICATUS) to classify activities into different categories. Activities are classified into 165 distinct categories, which provide us with detailed information on the activities performed by household members. Using the description of activities, we classify an activity as being performed indoors or outdoors, relying on the categorization proposed by Graff Zivin and Neidell (2014). Specifically, we classify an activity as being performed only outdoors if no part of the activity unambiguously can be performed within the indoor premises, which enables us to construct the measure of time spent outdoors for each household member.[1] We are, therefore, able to construct a measure of time spent on activities that are performed outdoors for each household member for whom time-use information is available, i.e., those aged six years and above. We then combine these observations with the data on air pollution and weather conditions for the district in which the household resides. If and how the individuals reallocate the time spent on outdoor activities when exposed to different levels of ambient air pollution, hence illustrates the form of undertaken avoidance behavior. 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 actively participate in the labor market and have a greater say in allocating 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, which provides 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 reported timeframe. Our main pollutant of interest is $PM_{2.5}$ - the particulate matter that is 2.5 micrometers or smaller in diameter. Because of their extremely small size, they can penetrate deep into human tissue and cause multiple obstructions to normal functioning. Existing studies, both in the economic and epidemiological literature, have shown robust and consistent negative effects of $PM_{2.5}$ exposure on health and other outcomes (Aguilar-Gomez et al., 2022). Elevated levels of $PM_{2.5}$ can result in smog and other environmental phenomena that are visually perceptible. This may

[1] The description of activities classified as outdoors is presented in Table A1.

prompt residents of the polluted area to change their time allocation across various activities, especially those that are performed outside. This study aims to empirically test this hypothesis.

To uncover the causal effect of air pollution exposure on time-use patterns, we use an instrumental variables (IV) setup. We rely on an IV design to secure the identification against potential measurement errors in the pollution exposure measure and the possible presence of omitted variables. We instrument for district-level $PM_{2.5}$ concentration measure with an interaction of the district to be in one of the district clusters and the wind direction to be in one of the four 90° bins in the spirit of Deryugina et al. (2019). This IV strategy provides plausibly exogenous variation in air pollution concentration driven by idiosyncratic changes in local wind directions. 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 requirement of information on local polluting sources' precise locations. 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. Although the data preclude us from testing this assumption directly, we establish the validity of our instruments via multiple falsification checks. We also show that instruments based on wind directions have a strong first-stage for our main specifications.

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. A juxtaposition with OLS results, which are lower in magnitude and weaker in statistical significance, compels us to presume that the abovementioned limitations might conflate the OLS estimates. It is noteworthy 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 altered neither from restricting the sample to days that the survey considers as "normal", nor from dropping extreme values of time spent on activities that are performed outdoors, nor from 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 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 finding 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]. We find that on more polluted days, the share of male members' time on activities related to unpaid care that are performed outdoors increases. We also find that the share of female members' time on activities related to self-care and maintenance outdoors goes up on more polluted days. These findings imply that elevated levels of air pollution might lead to more equitable intrahousehold distribution of activities related to unpaid care. These conclusions are further bolstered by a more pronounced decline in time spent outdoors for single-member households, as the margin for an increase in outdoor activities related to unpaid care might be absent for such 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 the employment of college-educated people 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 find 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.[4] Thus, we would expect to see a more pronounced effect on these subpopulations. The absence of the effect for respondents with regular wages ties well with reduced time being mostly driven by employment-related outdoor activities due to their inflexibility in labor supply decisions in the short run. The lack of such flexibility does not provide a priori enough margin to reallocate time away from outdoor employment activities. We show that an average respondent in our sample with a potential flexible labor supply schedule is willing to pay 6.8% of their daily wages to improve the air quality to a level considered safe by the World Health Organization (WHO).

We find that the 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 is driven by the respondents who have flexible labor supply arrangements, we should not expect to see any difference in the baseline effect among different days of the week. Our results support

[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.

[4]We note that the effects that we highlight are for short-run allocation of time on various activities. In the medium- to long-run, respondents with these usual principal activity statuses may not be able to detach themselves from the labor market.

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 outdoors.

The closest to our work is Bäck et al. (2013), Graff Zivin and Neidell (2009), Neidell (2009), and Moretti and Neidell (2011)[5]. All four 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, 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) illustrates 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[6,7]. To the extent that there are non-linearities in the response function of time-use to air pollution concentrations, the estimates from the abovementioned studies might not be a reliable guide in more polluted settings. Second, we do not restrict our analysis sample to small geographical settings - we use data on all districts in India to provide nationwide estimates. Third, due to our large sample size, we have enough statistical power to document changes in time allocation not only to different activities but also to determine whether this allocation is differentially affected for various subpopulations. Finally, our identification strategy is different from these works. Specifically, we use an IV setup relying on changes in air pollution levels generated by changes in local wind direction. These earlier works rely on variations in smog alert dissemination generated by previously determined arbitrary concentrations of pollutants in a regression discontinuity setup.

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 (Wang and Zhang, 2023; Ito and

[5]To tackle the understatement of costs, measurement error, and omitted variables bias, Moretti and Neidell (2011) use boat traffic in Los Angeles port as an IV for ozone concentrations, and estimate the costs of avoidance behavior.

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

[7]"India is among the most polluted areas of the world" - Andreas Uppstu, per Reuters.

Zhang, 2020; Saberian et al., 2017; Bäck et al., 2013; Moretti and Neidell, 2011; Graff Zivin and Neidell, 2009; Neidell, 2009). Building on these existing works that 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 to the literature that examines the effect of exposure to short-run changes in weather conditions on time-use patterns (Garg et al., 2020; Graff Zivin and Neidell, 2014; Connolly, 2008). 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) by showing that during higher polluted days, male members of the households reallocate their time to unpaid care activities, which in turn allows the female members to spend more time on leisure. Consequently, although air pollution exerts large negative effects on various outcomes, it might have an unintended consequence on equalizing intrahousehold allocation on unpaid care activities by gender, i.e., reducing the gender gap in this regard. Fourth, we contribute to a large literature studying the 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 rich body of literature on the determinants of labor supply (Behrman, 1999), to which we add plausibly exogenous increases in air pollution.

The rest of this paper is organized as follows. In Section 2, we display the employed data and provide summary statistics for our analytical sample. In Section 3, we illustrate the empirical strategy and discuss the threats to identification. We then present results in Section 4. Section 5 provides a discussion of 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 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 survey - India Time-Use Survey (ITUS) in 2019. We rely on satellite reanalysis data to obtain 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 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 activities classified as outdoors in Table A1.[8] We note that the household members allocate a large fraction of the time spent outdoors on the production of goods (and services) either for their own final use or in household enterprises, whereas some fraction is allocated for leisure activities. For the activities that are equivocal in the

[8] In Table A19, we show that our main results are robust to using the survey definition of whether the activity is performed "within premises of the dwelling unit of the selected household". Furthermore, classifying activities as being performed outdoors, where the description suggests that most tasks are done outdoors ("Relaxed Classification"), does not substantially alter our conclusions.

description, whether they are performed outdoors, indoors, or a 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, available at a high spatial and temporal resolution. In particular, we use data that have 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). It should be noted that satellite reanalysis data have been shown to underestimate the actual pollutant concentrations at higher levels in contrast to monitor data (Fowlie et al., 2019). Therefore, to the extent that we find a negative effect of air pollution exposure on time spent outdoors, our estimated effect is a lower bound of the true effect of air pollution exposure on time spent outdoors. In Figure A1, 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 our 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 the data that have a horizontal resolution of approximately 9 km ($0.1^{\circ} \times 0.1^{\circ}$) and hourly temporal resolution. We use the data on surface temperature, precipitation, and wind speed.

2.3 Analytical Sample Construction

This subsection describes how we combine survey data on time-use and satellite reanalysis data on air pollution levels and weather conditions. To combine these distinct sets of data, we perform a matching exercise using districts as the spatial units. We use information on the district of residence for the household in the ITUS data. To construct district-level measures of air pollution concentrations and weather conditions, we use district-level shapefiles extracted from the Housing and Population Census of 2011. It should be noted that ITUS data were collected in 2019, whilst many new districts have formed since 2011 by collapsing previous states or districts. In order to obtain information on all districts in the ITUS data, we manually determined the parent district in 2011 shapefiles data for each district that was newly created between 2011 and 2019. Therefore, we can construct measures of air pollution and weather conditions for each district that we observe in ITUS data. We construct measures of each pollutant by weighting each grid that intersects the district polygon by the extent of its overlap. We do this for each time layer observed in the CAMS EAC4 data. In order to construct the air pollution measures relevant to the 24-hour time period over which the activities are recorded, we take the average of the eight three-hour measures in the relevant 24-hour period. Therefore, we create a daily measure of air pollution concentrations for each of our pollutants. We follow a similar scheme to construct weather measures from ERA5-Land data, whereby the only difference is that we average all 24 hourly measures within the relevant ITUS 24-hour time period. Finally, we combine the daily measures of air pollution and weather conditions at the district-level with the ITUS data using the information on the district of residence of the household. It should be noted that we do not have survey data information for 951 households, which prevents obtaining pollution exposure for these households. Therefore, in our analysis, we drop observations on these households.

2.4 Descriptive Statistics

Hereby, we introduce descriptive statistics for our main analytical sample. We start by presenting basic descriptive statistics for the individual- and household-level variables. We present the number of observations with non-missing information, mean, standard deviation, minimum and maximum value for each variable. These are presented in Table 1. In order to account for complex survey design, we weight our observations according to the weights provided by the National Sample Survey Organization (NSSO) 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. 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 outdoors. In Figure

1, we present the mean $PM_{2.5}$ concentration and associated 95% confidence intervals for each day of the year.[9] 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 2, 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 2, 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 outside pollution level is high. 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

We start discussing our empirical strategy by detailing a fixed-effects specification, which we estimate using Ordinary Least Squares (OLS). 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 enforce an instrumental variable (IV) setup and discuss identification along with the estimation of this specification. Furthermore, we discuss threats to identification in our instrumental variable setup.

We estimate the following specification using OLS:

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

This specification includes fixed-effects for the district of residence and time, whereby time fixed-effects, $\alpha_{i(t)}$, enter the specification through fixed-effects for day-of-year and day-of-week, and the district of residence fixed-effects, $\alpha_{i(d)}$, control for time-invariant district-level observable and unobservable characteristics, suchlike the topography of the district. Time fixed-effects control for observable and unobservable factors common to all districts on a given day of year and week. 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

[9] Table A2 presents descriptive statistics for the pollution and weather conditions.

estimates as we will misattribute the effect of such factors on time-use to air pollution. We also control for weather conditions that might be correlated with air pollution concentration and time-use in $\mathbf{W}_{i(d,t)}$. This vector of weather conditions include precipitation, temperature, and wind speed. 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 the 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 characteristics, the estimated effect of air pollution exposure on time spent on various activities may still be biased. This could happen due to either the measurement error in the pollution exposure or unaccountable omitted [time-varying] variable bias (OVB). While we assign district-level air pollution levels to all households in a given district, this may not be the perfect measure of air pollution exposure for each household. Conceivably, air pollution varies within districts, thereby leading to measurement error in the pollution concentration measure. As long as the measurement error in air pollution concentrations is not systematically related to time-use patterns, our estimated effect of air pollution exposure on time allocation will be an underestimate of the true effect. OVB might also lead to biased estimates, whereas the direction of the bias would be ambiguous.

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.

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

In Equation (2), all parameters are the same as in Equation (1) except for $\theta_{k,b}$ which is the parameter on the interaction of an indicator variable for the district of residence d to be in cluster k, $\mathbb{1}\left(i(d) \in k\right)$, 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 classify districts. In Figure A2, 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 $[0°, 90°]$. 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 the local time-varying unobservables that jointly affect time-use patterns and air pollution levels. Moreover, in our setup, the same wind direction can differentially affect the wind direction in various district clusters. In Figure 3, we illustrate this by showing that the same wind direction affects air pollution concentration differently in two distinct district clusters. Since we use two-stage least squares estimation for our IV specifications, the second-stage is given by the following specification:

$$y_i = \alpha_{i(d)} + \alpha_{i(t)} + \beta \widehat{PM2.5}_{i(d,t)} + \mathbf{W}_{i(d,t)}\pi + \mathbf{X}_i\gamma + \mathbf{X}_{i(h)}\delta + v_i \tag{3}$$

In Equation (3), all parameters are the same as in Equation (1) except for $PM_{2.5}$ which is now predicted in the first-stage and denoted by $\widehat{PM2.5}$. We next discuss results from 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 3. 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 one 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 A3, 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 3. In the following four columns, we use information on the type of 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, for any reason, the respondent cannot perform their routine activities, the corresponding day is designated as "other". Weekly off-days, holidays, and days of leave are also designated as "other" days. Our point estimates suggest that the main effect is not sensitive to restricting the sample to "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 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 A3, 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 (Jin et al., 2022). 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 A3 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 of the number of interviews conducted at the district-level for that day. We then regress this measure on the $PM_{2.5}$ concentration, controlling for weather conditions, district, 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 A4. 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 A5. We conclude that our main effects are not confounded by the presence of other pollutants that might be correlated with $PM_{2.5}$.[10] In Table A6, we establish that our main effect of reduced time on outdoor activities is similar across the particulate matter of different sizes.

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

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 a 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 A7. 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 our estimated effect of air pollution exposure on time spent outdoors. 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 A3. 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 A4. 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 4. 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 an effect on the lag of pollution measures 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 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 5. 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 5. We find that the reduction in time spent on outdoor activities is more pronounced for those respondents who identify as male relative to those who identify themselves as female. In the following four columns, we examine if the estimated effect of air pollution exposure on time spent on activities 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 residing in 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 the 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 below median UMCE households. This finding echoes the results 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%. This result also confirms the findings in earlier work documenting low adoption of air purifiers and other defensive investments and actions for medium- and high-SES homes (Greenstone et al., 2021). 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 residents of rural areas drive our main effect. This finding is par for the course, provided the apparent socioeconomic gap between rural and urban areas, more flexible work schedules, and a 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[11]. The second group consists of activities related to producing goods for own final use[12]. The last two groups consist of activities related to unpaid services and leisure.[13] We present results from examining the differential effect of air pollution exposure on time spent on activities within these four groups in Table 6. 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 outdoor activities related to unpaid care leads to intrahousehold substitution from females to males for these activities. We also show that the respondents' age does not drive the effect observed for outdoor activities related to employment. In Table A8, we show that our result on employment-related outdoor activities is unaltered by using all the respondents above the age of six.

We examine which activities performed outdoors related to employment drive the reduced time outdoors. Our point estimates in Table A9 point to activities related to agriculture that are performed outdoors are chiefly responsible for reduced time outdoors on activities related to employment. In order to highlight the activities related to unpaid care that are performed outdoors, to which reduced time outdoors from employment related activities is reallocated, we examine two- and three-digit activity codes related to such activities in Table A10. Our results show that time on activities performed outdoors, which are related to unpaid domestic services involving travel related to goods and household members, leads to increased time outdoors on activities related to unpaid care. In Table A11 - A13, we uncover the activities related to leisure that lead to increased time spent indoors arising due to reallocation from time saved forgoing outdoor activities. Our results suggest that the increased time indoors related to leisurely activities emanates from increased time spent socializing and communicating and greater use of mass media. Overall, these results suggest that on exposure to elevated levels of air pollution, people respond by reducing time spent outdoors on activities related to employment. 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 households with at least one male and one female member. We then construct a measure of male members' share of time spent on four broad groups of activities discussed previously for Table 6. 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 household

[11]These activities have one as the first digit in the 3-digit activity code.

[12]These activities have two as the first digit in the 3-digit activity code.

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

members spent on various activity groups. We present results from estimating these specifications in Table 7. 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 intrahousehold 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 find robust evidence for increased time allocated for leisure activities performed outdoors for female members of the household relative to male members. We also show that this effect is not driven by spillover to unmarried household members. In Table A14, we restrict the estimating sample to currently married household head and their spouse. We find that within the household, reallocation of time across male and female household members is similar to our main estimating sample without this restriction. 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 A15. 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 performed outdoors between male and female household members.

In order to tease out specific activities towards which male household members increase their share of time spent, we examine finer categories related to unpaid care activities in Table A16 and leisure in Table A17. Our results in these two tables indicate that the increased male share of time spent on activities related to unpaid care that are performed outdoors is due to activities related to shopping for household and family members. The decline in the male share of activities related to leisure that are performed outdoors is driven by activities related to self-care and maintenance. 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 providing unpaid care within the household (Vyas, 2021).

We now discuss if the effect of air pollution exposure on time spent on activities performed outdoors differs by the respondent's age. 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 at least six but below 22 years of age.

These are respondents who are most likely to be in school or college. The second group consists of respondents who are between the ages of 23 and 45 years and are actively participating in the labor market. The third group consists of respondents between the ages of 46 and 60. The final group consists of respondents who are above the age of 60. We present results from estimating the specifications that we outlined above for these four groups in Table 8. We find that our main effect of reduction in time spent on activities performed outdoors is driven by the decline in time spent on activities 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 6. Since employment-related activities mainly drive the baseline effect, the heterogeneous effect for active labor market participants verifies the logical double-checking.

We next turn to discuss if respondents with different levels of education drive our main effect of reduced time spent on activities that are performed outdoors. We restrict our estimating sample to those above 23 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 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 comprises respondents who have completed primary school education. The third and fourth groups consist of those respondents who have completed above primary school and college, respectively. We present the results in Table 9. We find that the effect of air pollution exposure on time spent on activities that are performed outdoors monotonically decreases as the respondent's level of education increases. The most pronounced effect is found for illiterate respondents. 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 stringent working requirements, the absence of the effect is anticipated.

We next discuss if the effect of air pollution exposure on time spent 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 employed respondents, we construct three mutually exclusive and exhaustive groups - 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 10. Our results show that our main effect is driven by respondents who report their usual principal activity status as 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 short-run labor supply decisions for this subpopulation does not provide enough margin to reallocate time spent on employment-related outdoor activities. 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 work industry for respondents who report being employed as their usual principal activity status to define an industry in which the respondent is employed as being high-risk or not. ITUS provides 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 agriculture, forestry, fishing and hunting, mining, construction, manufacturing, transportation, and utilities. We present results in Table 11. 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 straightforward.

We now discuss if our estimated effect of air pollution exposure on activities 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 A5. Point estimates from our preferred IV specifications suggest 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 regarding 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 2, 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 because of high pollution levels. We present results from estimating our main specifications by restricting the estimating to five distinct regions in Table A18. 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 as 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 12. 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 these monitors, and existing monitors provide intermittent information about air quality due to frequent outages.

Information provision, nonetheless, is not the only mechanism that constitutes the list of possible factors linking pollution exposure to avoidance behavior. Direct health effects and air clarity play an important role when deciding whether to stay within indoor premises on highly polluted days. In this regard, extremely high $PM_{2.5}$ levels should cause relatively more drastic deterioration in health conditions and more visual impairment, consequently leading to higher magnitude in the main estimates. To test this assumption, we examine if the baseline effect is non-linear. Particularly, we modify specifications in Equations (1) - (3) 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 13. While our point estimates suggest a substantially larger effect of air pollution exposure on time spent outdoors, the effect is only marginally statistically significant since there are only a few days in a year with an average $PM_{2.5}$ higher than 100 $\mu g/m^3$[14]. Thereby, we exercise caution in explaining this finding as existence for convexity whereby higher concentrations of air pollution cause even more time to be reallocated to indoor activities. Additionally, due to the data limitations, we are unable to directly test the deterioration in health conditions as the pathway for the causal impact of air pollution on avoidance behavior.[15] We can only rely on existing literature about the effect of pollution on health. Hence, the combination of our analysis and existing literature demonstrates that the role of direct health consequences and visibility in the air as causal mechanisms in our investigation is feasible.

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 intervals. We construct a measure of air pollution exposure using satellite reanalysis data on $PM_{2.5}$ concentrations. We leverage changes in local wind directions in an IV setup to uncover the causal effect of air pollution exposure on time-use patterns. 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 spent on activities performed outdoors, a 4.4%

Additionally, our effects are heterogeneous across subgroups and broad categories of activities. We find that the main effect of reduced time 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 reallocation results from the decline in time spent on employment outdoors. Further, this time saved from employment-related outdoor activities is reallocated to leisure-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. Notably, 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 assumes a greater weight in a developing country setting like ours where the burden of such activities often disproportionately falls on female members of the household (Deshpande and Kabeer, 2021). However, such potentially unintended benefit of elevated pollution levels might come at significant monetary costs due to lost earnings to the extent reduced time outdoors emanates from reduced labor supply. Furthermore, this finding points to female members' limited intrahousehold bargaining power in

[14] Approximately 25% of our sample has $PM2.5$ concentration level above 100 $\mu g/m^3$.

[15] In Table A20, we show that the time spent on activities related to health does not change significantly on exposure to elevated levels of air pollution.

driving initial within household distribution of unpaid care activities.

We observe that the main effect is declining monotonically with the respondent's education level. We also show that the reduction in time spent 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.

There could be multiple channels through which air pollution exposure may reduce the time spent on activities that are performed outdoors. For instance, better information might lead to reduced time outdoors. Moreover, it might also be the case that exposure to air pollution worsens health, and exposed residents are incapacitated, reducing their time outdoors. Finally, perceptible changes in air pollution levels, like visual impairment, affect how people allocate their time. While our data precludes us from testing for all these mechanisms, we rule out information provision as the likely channel driving our main effect.

In order to quantify the marginal willingness to pay for air quality improvements, we refer to the World Health Organization (WHO) 24-hour safe $PM2.5$ limit of 15 $\mu g/m^3$ (WHO, 2021). We note that most of the reduced time outdoors stems from activities related to employment that are performed outdoors (Table 6). Therefore, assuming the linearity of the dose-response function for the time reallocation, an employed respondent is willing to forego almost 6.8% of their daily wages on average to improve air quality that is considered safe according to the WHO standards.[16]

Our results have major implications for the behavioral responses of residents of developing countries that contend with very high air pollution levels. Many of the residents of these countries do not have access to affordable technologies to dampen their exposure to elevated air pollution. In the absence of such technologies, they rely on costly avoidance behavior by reallocating their time used on various activities, often by reducing their labor supply and forgoing significant earnings. While our data precludes us from providing evidence for relatively lower ambient air pollution levels indoors, such air pollution disparity between indoors and outdoors might be the primary reason for residents to reduce their time outdoors. To the extent that there are other margins over which the residents of polluted regions limit their air pollution exposure, our findings might be interpreted as the lower bound estimates of avoidance behavior. Without ambient air quality improvements, the behavioral margin we document might become more important. This will be the case if the availability of cheap air purification technologies widens the disparity between indoor and outdoor air quality, which might induce residents to spend more time indoors.[17] Further, we also note that by reducing their time outdoors, residents of highly polluted regions might also suffer from deleterious health effects due to inactivity, over and above the widely documented negative health effects of air pollution exposure.

[16] The calculation is as follows: $\frac{(83.982-15)*(-0.099)}{99.66} \approxeq -0.068$. In this calculation, 83.982 is our sample's average $PM2.5$ concentration, as documented in Table A2. -0.099 is the marginal effect of a one microgram per cubic meter change in $PM2.5$ concentration on outdoor activities related to employment from Table 6. Finally, 99.66 is the average time spent on employment related activities outdoors from Table 6.

[17] However, as outdoor air quality in these countries improves the type of avoidance behavior that we document may become less important.

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. Furthermore, we highlight the short-run intensive margin of labor supply decision in the wake of transitory air pollution shock. Our data precludes us from investigating extensive margin of industrial or occupational choice, which may be important, especially for long-term exposure to air pollution.[18] Identifying these and other margins of adjustment due to air pollution exposure may constitute a fruitful area of research.

[18]In Table A21, we establish the robustness of our main finding to include NIC 2008 classification two-digit codes. These results highlight that our results are not conflated by changes in the employment industry by the survey respondents.

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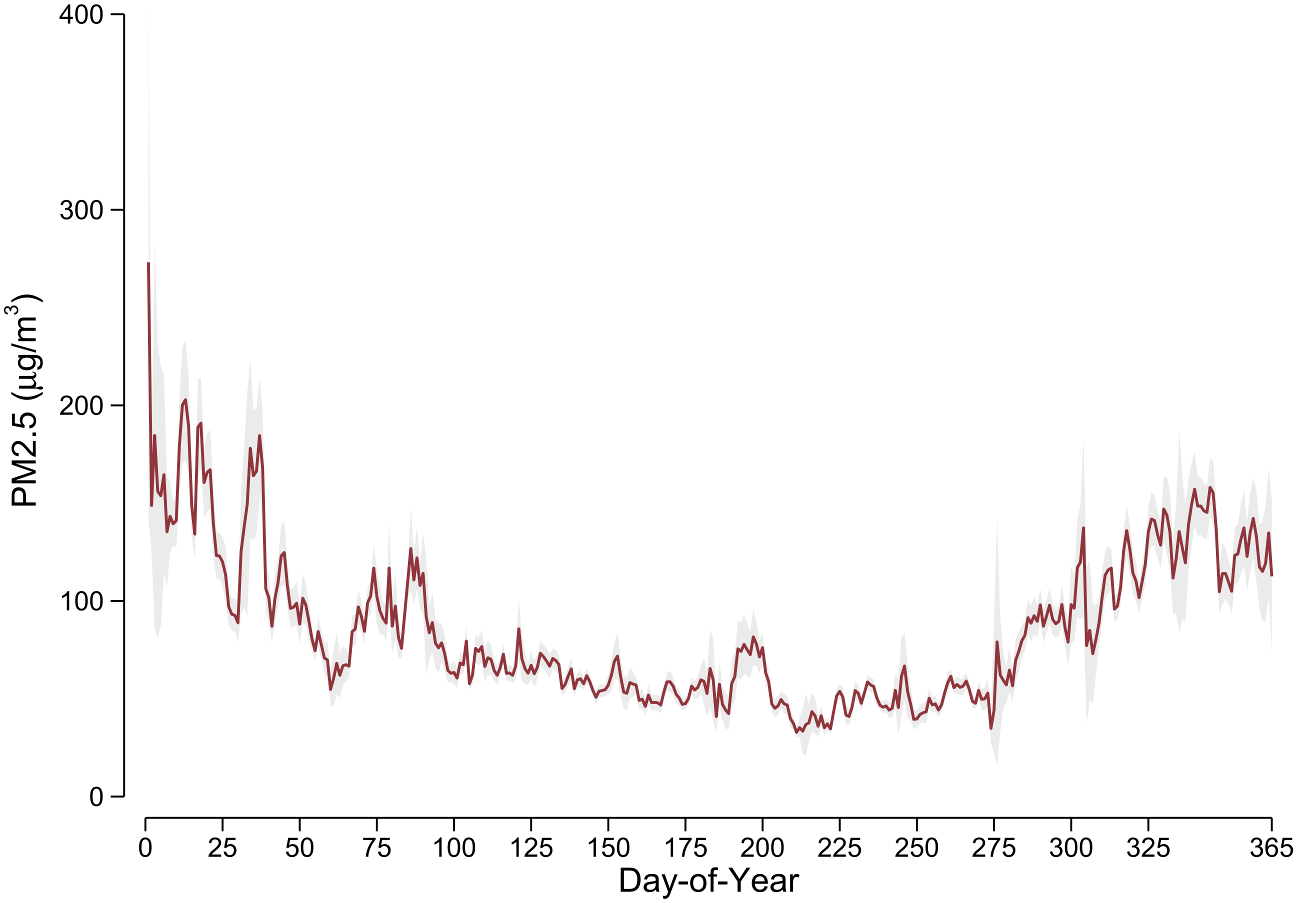
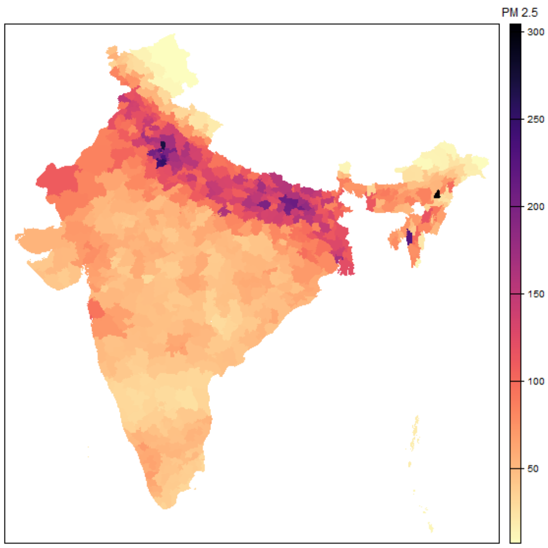
Figure 1: Temporal Variation in $PM_{2.5}$ Concentration

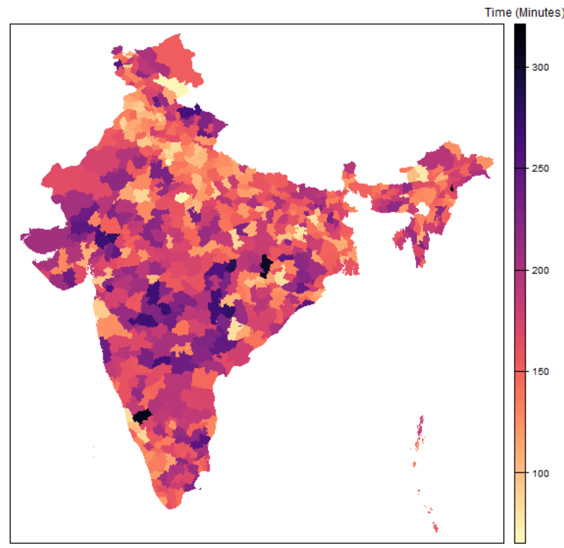


Note: Data on $PM_{2.5}$ concentration comes from CAMS-EAC4 satellite reanalysis data provided by the European Centre for Medium-Range Weather Forecasts (ECMWF). The mean $PM_{2.5}$ concentration across all districts for each day of the year, along with the 95% confidence interval, is plotted.

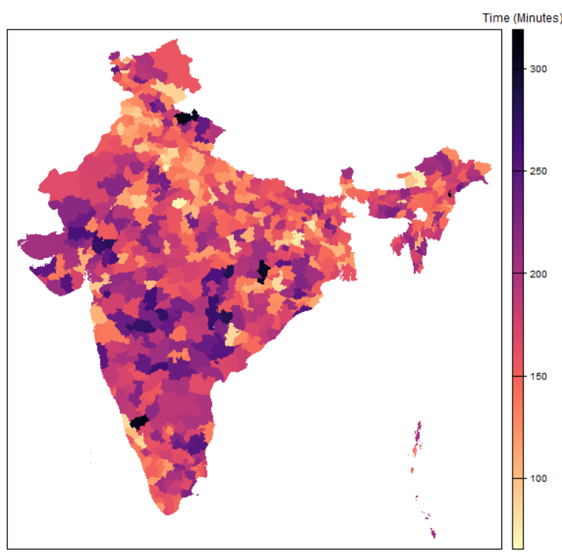
Figure 2: Spatial Variation in $PM_{2.5}$ Concentration and Time-use



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



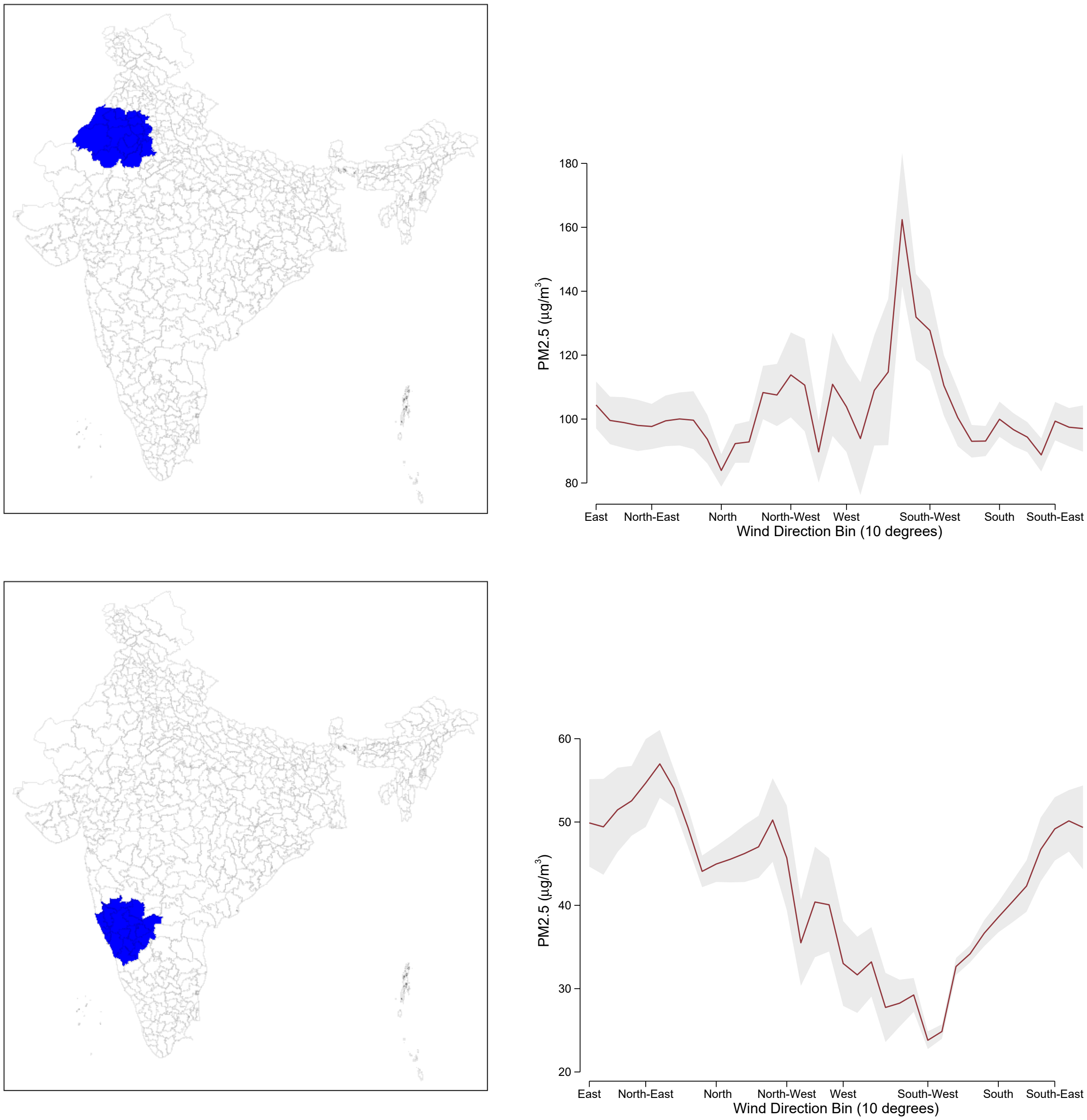
(b) Time on Outdoor Activities: Both Major and Minor Activity



(c) Time on Outdoor Activities: Only Major Activity

Note: Data on $PM_{2.5}$ concentration comes from CAMS-EAC4 satellite reanalysis data provided by the European Centre for Medium-Range Weather Forecasts (ECMWF). $PM_{2.5}$ concentration is averaged over all the days on which at least one interview is conducted in the district. Time on outdoor activities in the last two panels is in minutes. Time on outdoor activities is averaged for all the respondents in a given district. The average in all the three panels is unweighted. The second panel uses time division where the time on all activities in time interval is distributed equally among the activities in that time interval. The last column allocates time in a time interval only to the "major" activity reported by the respondent for that time interval. The district polygons come from the 2011 Census of India.

Figure 3: Instrument Motivation



Note: This figure shows two distinct clusters of districts. The panels on the right suggest that the same wind direction influences air pollution levels differently for these two clusters. For instance, wind from the southwest increases pollution levels in the top cluster but reduces the air pollution levels in the bottom cluster.

Table 1: 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

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 2: Time Spent on Indoor and Outdoor Activities

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

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

Table 3: Effect of Air Pollution on Time Spent Outdoors – Main Effect

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	OLS	OLS	OLS	OLS	OLS	IV	OLS	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 4: 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				
$PM2.5\left(\mu g/m^3\right)$	-0.028	-0.094	-0.007	-0.143
	(0.012)**	(0.034)***	(0.011)	(0.063)**
$PM2.5\left(\mu g/m^3\right)$ Lag			-0.006	0.006
			(0.011)	(0.063)
$PM2.5\left(\mu g/m^3\right)$ 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				
$PM2.5\left(\mu g/m^3\right)$	-0.028	-0.087	-0.010	-0.139
	(0.012)**	(0.034)***	(0.011)	(0.067)**
$PM2.5\left(\mu g/m^3\right)$ Lag			-0.006	-0.007
			(0.011)	(0.065)
$PM2.5\left(\mu g/m^3\right)$ 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 5: 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 sub-population. 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 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																
$PM2.5\ (\mu g/m^3)$	0.019	-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 activity divisions based on the first digit of the 3-digit activity code from ICATUS 2016 are further classified into four major divisions. The column headings indicate which one-digit activity codes are grouped together. Each specification in all columns includes 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 7: 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 surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The sample includes households that have at least one male and female member. The dependent variable in all columns is the ratio of time spent on outdoor activities in minutes by male to female members of the households. Activities classified as outdoor are discussed in the main text. Nine activity divisions based on the first digit of the 3-digit activity code from ICATUS 2016 are further classified into four major divisions. The column headings indicate which one-digit activity codes 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 8: 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 9: 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
	Illiterate		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. 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 10: Effect of Air Pollution on Time Spent Outdoors: Heterogeneity by Usual Principal Activity Status

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	Self-Employed		Regular Wage/ Salaried Employee		Casual Labor		Unemployed or Not in Labor Force	
Panel A: Both Major and Minor Activity								
$PM2.5\,(\mu g/m^3)$	-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								
$PM2.5\,(\mu g/m^3)$	-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. 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 highest education level. 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: 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 12: 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 13: Effect of Air Pollution on Time Spent Outdoors: Non-Linear Effects

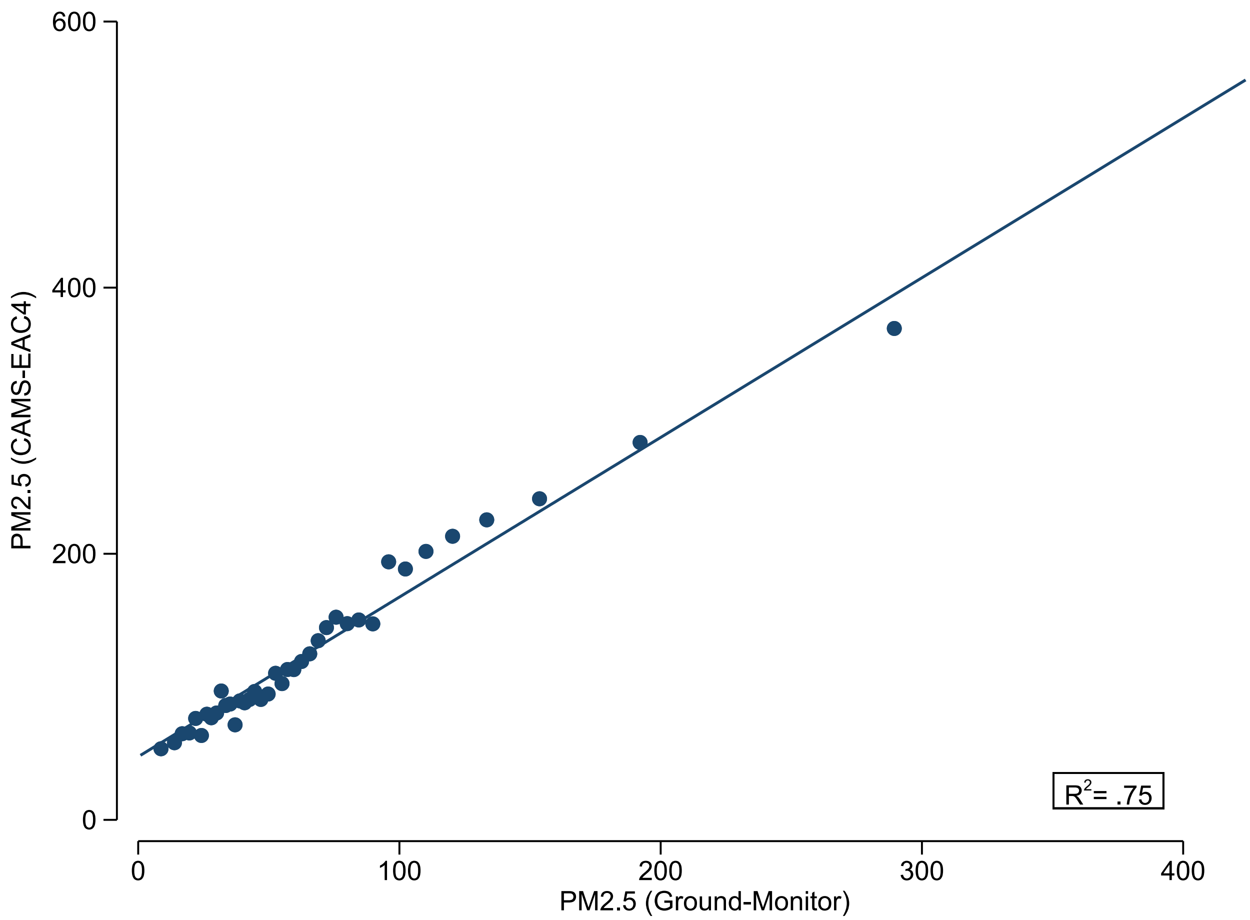
	(1) OLS	(2) IV	(3) OLS	(4) IV
	Baseline		High PM2.5	
Panel A: Both Major and Minor Activity				
$PM2.5\,(\mu g/m^3)$	-0.028	-0.094		
	(0.012)**	(0.034)***		
$PM2.5\,(\mu g/m^3) > 100$=1			-2.709	-11.565
			(2.109)	(6.291)*
Adj. R2	0.357	0.321	0.357	0.321
Dep. Var. Mean	157.875	157.875	157.875	157.875
KP F-Statistic		16.711		24.767
N	314,125	314,125	314,125	314,125
Panel B: Only Major Activity				
$PM2.5\,(\mu g/m^3)$	-0.028	-0.087		
	(0.012)**	(0.034)***		
$PM2.5\,(\mu g/m^3) > 100$=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

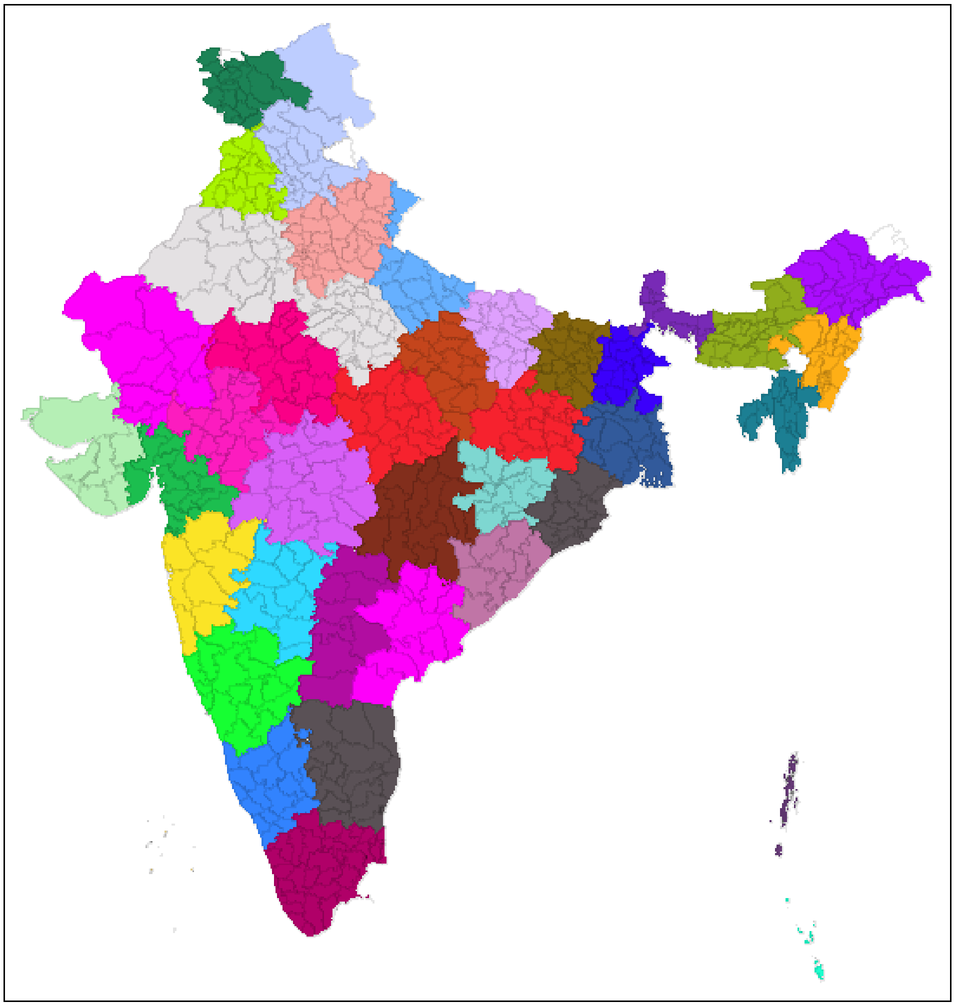
Appendix A Figures and Tables

Figure A1: Correlation between Ground Monitor and CAMS-EAC4 Data



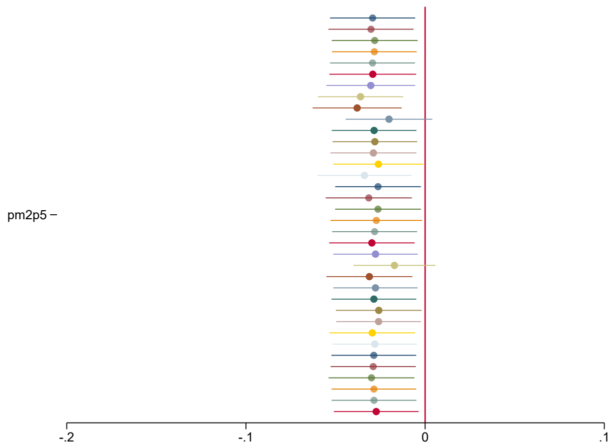
Note: Data for ground monitors $PM_{2.5}$ concentrations comes from the Central Pollution Control Board (CPCB), Ministry of Environment, Forest and Climate Change, Govt. of India Central Control Room for Air Quality Management. CAMS-EAC4 data is provided by the European Centre for Medium-Range Weather 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 A2: District Clusters

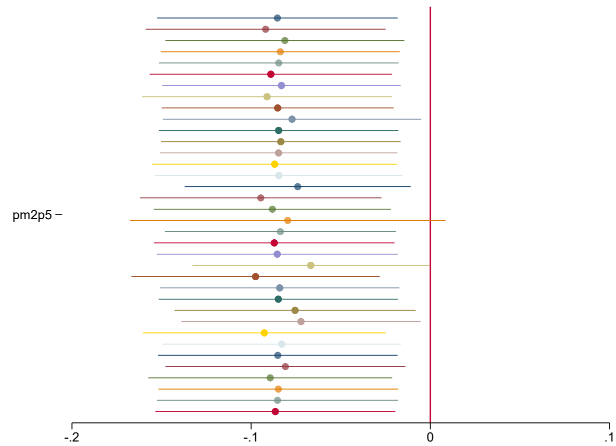


Note: Districts are classified into 40 distinct clusters using k-nearest neighbor algorithm with district centroid longitude and latitude used for classification. The district polygons come from the 2011 Census of India.

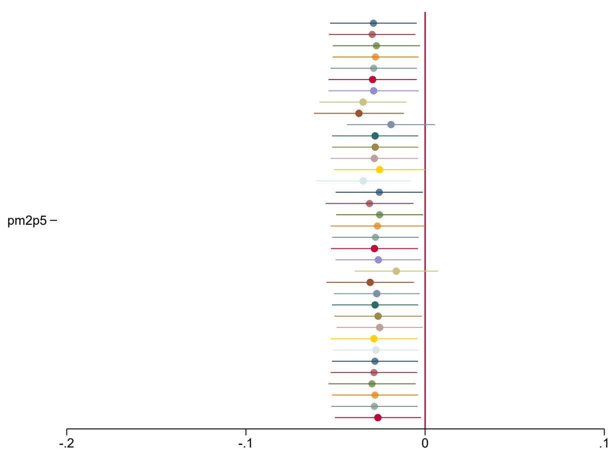
Figure A3: Robustness Check: Dropping one state at a time



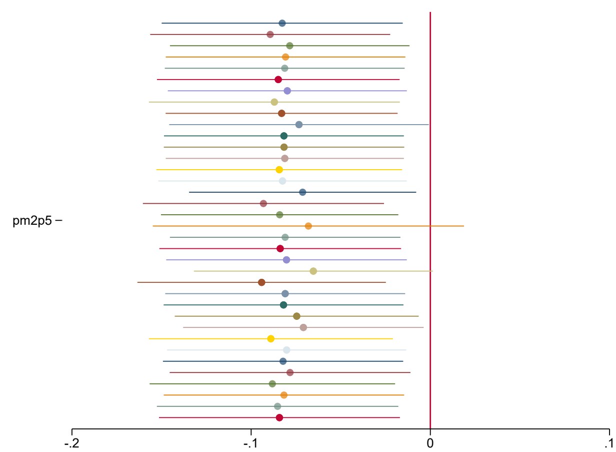
(a) OLS: Both Major and Minor Activity



(b) IV: Both Major and Minor Activity



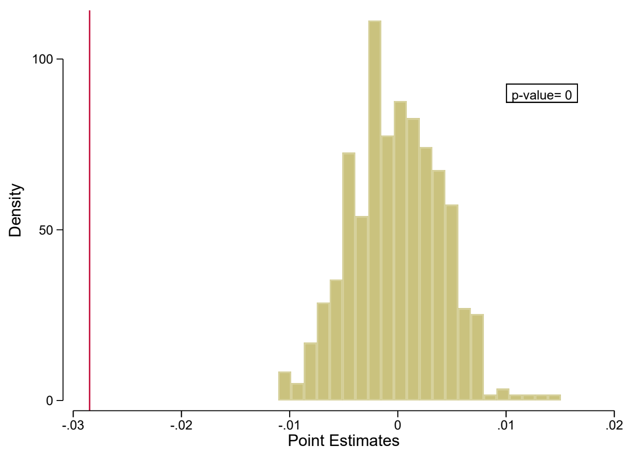
(c) OLS: Only Major Activity



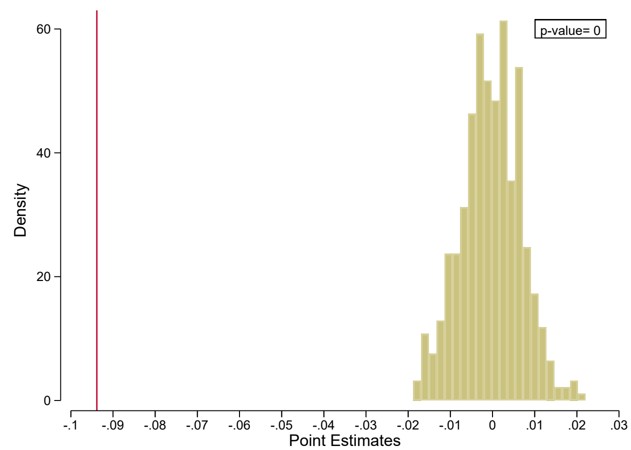
(d) IV: Only Major Activity

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.

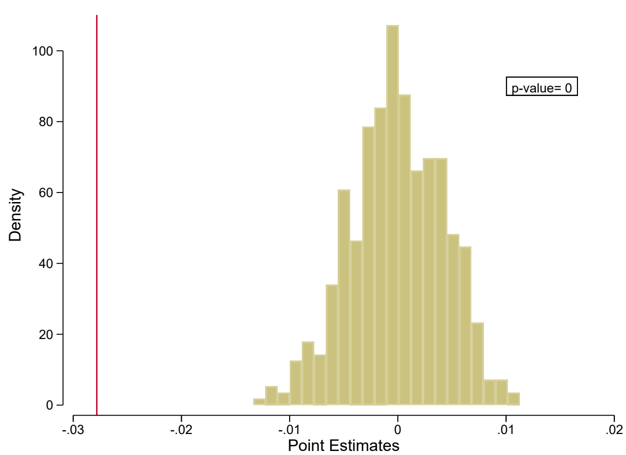
Figure A4: Placebo Check: Randomization Inference



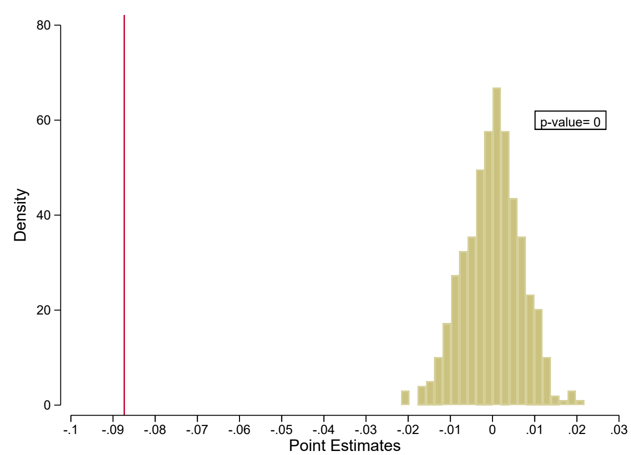
(a) OLS: Both Major and Minor Activity



(b) IV: Both Major and Minor Activity



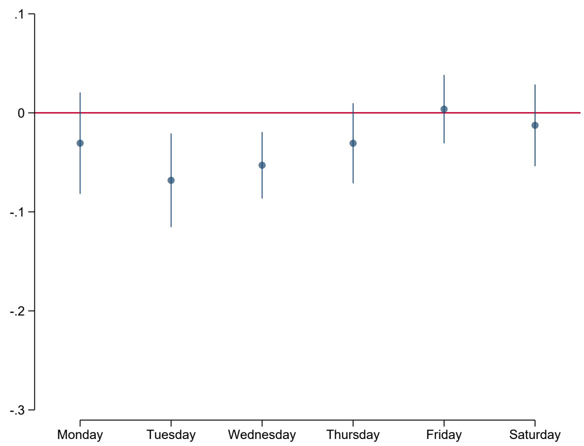
(c) OLS: Only Major Activity



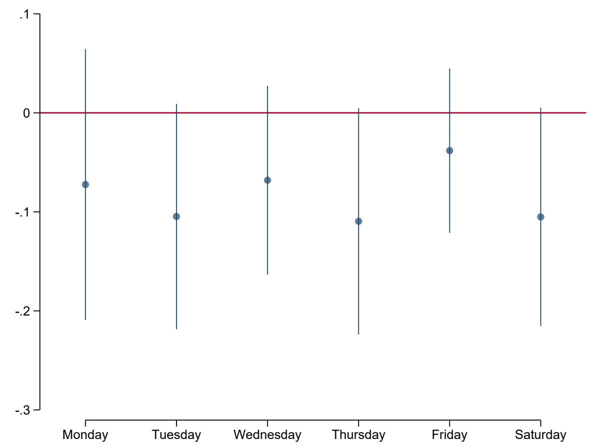
(d) IV: Only Major Activity

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.

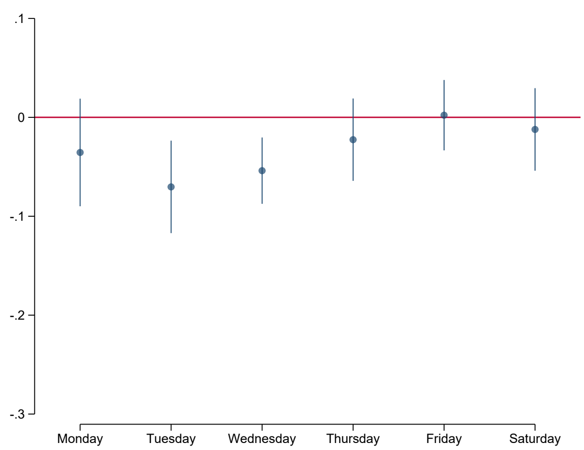
Figure A5: Heterogeneous Effects of Air Pollution on Time Spent on Activities that are Performed Outdoors: Day-of-Week



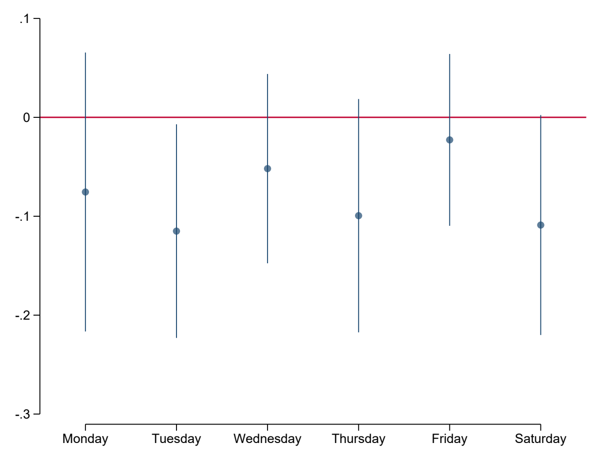
(a) OLS: Both Major and Minor Activity



(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 A1: 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 A2: Summary Statistics: Pollution and Weather Conditions

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

Notes: The sample 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. Pollution data is derived from CAMS-EAC4 satellite reanalysis data. Weather Conditions data is derived from ERA5-Land climate reanalysis data.

Table A3: Effect of Air Pollution on Time Spent Outdoors: Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	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 A4: 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 A5: Effect of Air Pollution on Time Spent Outdoors: Other Pollutants

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	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 A6: Effect of Air Pollution on Time Spent Outdoors: Other Particulate Matter Sizes

	(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 A7: Effect of Air Pollution on Time Spent Outdoors: Robustness to Alternate District Clusters

	(1)	(2)	(3)	(4)	(5)
	OLS	IV	IV	IV	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 A8: Effect of Air Pollution on Time Spent Outdoors – Effect by Major Activity Classification and Full Sample

	(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 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 A9: Effect of Air Pollution on Time Spent Outdoors – Employment Related Activities

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV
	Major Division 1 Employment and related activities		Code 12 Employment in household enterprises to produce goods		Code 121 Growing of crops for the market		Code 128 Construction activities for the market	
Panel A: Both Major and Minor Activity								
$PM2.5\left(\mu g/m^3\right)$	-0.046	-0.099	-0.041	-0.089	-0.038	-0.069	-0.000	-0.020
	(0.012)***	(0.033)***	(0.010)***	(0.029)***	(0.009)***	(0.026)***	(0.005)	(0.017)
Adj. R2	0.351	0.309	0.303	0.246	0.221	0.145	0.176	0.155
Dep. Var. Mean	99.663	99.663	62.524	62.524	39.862	39.862	17.307	17.307
KP F-Statistic		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
Panel B: Only Major Activity								
$PM2.5\left(\mu g/m^3\right)$	-0.046	-0.092	-0.042	-0.088	-0.039	-0.068	-0.000	-0.020
	(0.012)***	(0.033)***	(0.011)***	(0.029)***	(0.009)***	(0.026)***	(0.005)	(0.017)
Adj. R2	0.353	0.311	0.307	0.251	0.224	0.148	0.178	0.157
Dep. Var. Mean	103.226	103.226	65.103	65.103	41.465	41.465	18.012	18.012
KP F-Statistic		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

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The dependent variable in all columns is the amount of time spent on outdoor activities in the respective activity code. Activities classified as outdoor are discussed in the main text. The column headings indicate which activity codes are used for time-use computation. Each specification in all columns includes 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 A10: Effect of Air Pollution on Time Spent Outdoors – Unpaid Care Related Activities

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV	(9) OLS	(10) IV	(11) OLS	(12) IV
	Major Division 3,4,5 Unpaid care related activities		Code 3 Unpaid domestic services for household and family members		Code 4 Unpaid caregiving services for household and family members		Code 5 Unpaid volunteer, trainee and other unpaid and other work		Code 37 Shopping for own household and family members		Code 38 Travelling, moving or accompanying goods or persons	
Panel A: Both Major and Minor Activity												
$PM2.5\ (\mu g/m^3)$	0.007	0.017	0.008	0.015	0.000	0.000	-0.001	0.002	0.003	0.008	0.003	0.006
	(0.003)**	(0.007)**	(0.002)***	(0.006)**	(0.000)	(0.001)	(0.002)	(0.003)	(0.002)	(0.005)	(0.001)***	(0.002)***
Adj. R2	0.047	0.016	0.049	0.020	0.005	-0.001	0.075	0.004	0.032	0.008	0.022	0.003
Dep. Var. Mean	16.586	16.586	15.244	15.244	0.314	0.314	1.028	1.028	5.630	5.630	1.944	1.944
KP F-Statistic		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
Panel B: Only Major Activity												
$PM2.5\ (\mu g/m^3)$	0.008	0.018	0.008	0.015	0.000	0.000	-0.000	0.002	0.003	0.009	0.002	0.004
	(0.003)**	(0.008)**	(0.002)***	(0.007)**	(0.000)	(0.001)	(0.002)	(0.003)	(0.002)	(0.005)*	(0.001)***	(0.002)*
Adj. R2	0.038	0.009	0.038	0.010	0.004	-0.001	0.065	0.004	0.031	0.008	0.021	0.003
Dep. Var. Mean	15.559	15.559	14.213	14.213	0.328	0.328	1.018	1.018	6.044	6.044	1.866	1.866
KP F-Statistic		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

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The dependent variable in all columns is the amount of time spent on outdoor activities in the respective activity code. Activities classified as outdoor are discussed in the main text. The column headings indicate which activity codes are used for time-use computation. Each specification in all columns includes 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 A11: Effect of Air Pollution on Time Spent Indoors – Leisure

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV	(9) OLS	(10) IV
	Major Division 6-9 Leisure		Code 6 Learning		Code 7 Socializing and communication, community participation and religious practice		Code 8 Culture, leisure, mass media and sports practices		Code 9 Self-care and maintenance	
Panel A: Both Major and Minor Activity										
$PM2.5\left(\mu g/m^3\right)$	-0.001	0.093	-0.007	-0.033	-0.008	0.063	0.020	0.053	-0.007	0.010
	(0.014)	(0.037)**	(0.004)	(0.009)***	(0.012)	(0.032)**	(0.009)**	(0.025)**	(0.011)	(0.033)
Adj. R2	0.395	0.371	0.639	0.633	0.121	0.042	0.195	0.118	0.155	0.070
Dep. Var. Mean	983.786	983.786	27.449	27.449	128.978	128.978	123.607	123.607	703.753	703.753
KP F-Statistic		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
Panel B: Only Major Activity										
$PM2.5\left(\mu g/m^3\right)$	0.002	0.073	-0.007	-0.035	-0.007	0.015	0.023	0.046	-0.007	0.046
	(0.014)	(0.033)**	(0.004)*	(0.009)***	(0.010)	(0.023)	(0.009)**	(0.025)*	(0.012)	(0.034)
Adj. R2	0.402	0.380	0.642	0.636	0.123	0.048	0.179	0.109	0.141	0.065
Dep. Var. Mean	962.962	962.962	28.171	28.171	91.373	91.373	123.432	123.432	719.985	719.985
KP F-Statistic		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

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The dependent variable in all columns is the amount of time spent on indoor activities in the respective activity code. Activities classified as indoor are discussed in the main text. The column headings indicate which activity codes are used for time-use computation. Each specification in all columns includes 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 A12: Effect of Air Pollution on Time Spent Indoors – Leisure and One-Digit Activity Code 7

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
	Code 71 Socializing and communication		Code 711 Talking, conversing, chatting		Code 712 Socializing, getting together and gathering activities	
Panel A: Both Major and Minor Activity						
$PM2.5\,(\mu g/m^3)$	-0.008	0.058	-0.006	0.030	-0.003	0.022
	(0.011)	(0.031)*	(0.009)	(0.026)	(0.005)	(0.015)
Adj. R2	0.129	0.038	0.125	0.020	0.119	0.021
Dep. Var. Mean	112.484	112.484	92.029	92.029	17.709	17.709
KP F-Statistic		16.711		16.711		16.711
N	314,125	314,125	314,125	314,125	314,125	314,125
Panel B: Only Major Activity						
$PM2.5\,(\mu g/m^3)$	-0.009	0.004	-0.007	-0.017	-0.002	0.016
	(0.009)	(0.022)	(0.008)	(0.021)	(0.005)	(0.013)
Adj. R2	0.137	0.045	0.131	0.024	0.108	0.022
Dep. Var. Mean	74.750	74.750	55.349	55.349	16.936	16.936
KP F-Statistic		16.711		16.711		16.711
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 indoor activities in the respective activity code. Activities classified as indoor are discussed in the main text. The column headings indicate which activity codes are used for time-use computation. Each specification in all columns includes 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 A13: Effect of Air Pollution on Time Spent Indoors – Leisure and One-Digit Activity Code 8

	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
	Code 84 Mass media use		Code 85 Activities associated with reflecting, resting, relaxing	
Panel A: Both Major and Minor Activity				
$PM2.5\left(\mu g/m^3\right)$	0.014	0.052	0.010	0.007
	(0.007)**	(0.017)***	(0.007)	(0.020)
Adj. R2	0.207	0.114	0.198	0.051
Dep. Var. Mean	74.435	74.435	43.391	43.391
KP F-Statistic		16.711		16.711
N	314,125	314,125	314,125	314,125
Panel B: Only Major Activity				
$PM2.5\left(\mu g/m^3\right)$	0.019	0.043	0.008	0.007
	(0.007)***	(0.018)**	(0.008)	(0.021)
Adj. R2	0.174	0.098	0.187	0.050
Dep. Var. Mean	73.480	73.480	43.982	43.982
KP F-Statistic		16.711		16.711
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 indoor activities in the respective activity code. Activities classified as indoor are discussed in the main text. The column headings indicate which activity codes are used for time-use computation. Each specification in all columns includes 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 A14: Effect of Air Pollution on Time Spent Outdoors – Effect by Major Activity Classification and Male Share (Currently Married Sample)

	(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																
$PM2.5\ (\mu g/m^3)$	0.006	0.018	-0.000	-0.003	-0.002	-0.001	0.000	0.001	-0.006	-0.013	-0.001	-0.007	0.012	0.020	-0.005	-0.024
	(0.005)	(0.015)	(0.001)	(0.002)	(0.001)	(0.004)	(0.001)	(0.001)	(0.005)	(0.012)	(0.003)	(0.010)	(0.005)**	(0.011)*	(0.004)	(0.014)*
Adj. R2	0.135	0.044	0.042	-0.002	0.062	0.002	0.093	0.015	0.075	-0.000	0.146	0.021	0.102	-0.003	0.097	0.006
Dep. Var. Mean	45.474	45.474	0.793	0.793	6.551	6.551	50.197	50.197	67.149	67.149	14.235	14.235	16.831	16.831	16.633	16.633
KP F-Statistic		16.888		16.888		16.888		16.888		16.888		16.888		16.888		16.888
N	87,101	87,101	87,101	87,101	87,101	87,101	87,101	87,101	87,101	87,101	87,101	87,101	87,101	87,101	87,101	87,101
Panel B: Only Major Activity																
$PM2.5\ (\mu g/m^3)$	0.006	0.022	-0.000	-0.004	-0.002	-0.001	0.000	0.001	-0.007	-0.010	-0.001	-0.008	0.011	0.014	-0.006	-0.028
	(0.005)	(0.015)	(0.001)	(0.002)*	(0.001)	(0.003)	(0.001)	(0.002)	(0.005)	(0.012)	(0.003)	(0.010)	(0.005)**	(0.011)	(0.004)	(0.014)**
Adj. R2	0.135	0.045	0.033	-0.003	0.061	0.001	0.090	0.016	0.074	-0.001	0.146	0.021	0.098	-0.003	0.093	0.006
Dep. Var. Mean	45.122	45.122	0.690	0.690	6.323	6.323	50.286	50.286	66.555	66.555	14.002	14.002	16.497	16.497	15.589	15.589
KP F-Statistic		16.888		16.888		16.888		16.888		16.888		16.888		16.888		16.888
N	87,101	87,101	87,101	87,101	87,101	87,101	87,101	87,101	87,101	87,101	87,101	87,101	87,101	87,101	87,101	87,101

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique surveyed household. The sample is restricted to respondents between the ages of 18 and 60 who are currently married. 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 A15: 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 A16: Effect of Air Pollution on Time Spent Outdoors – Unpaid Care Activities Male Share

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	Major Division 3,4,5 Unpaid care related activities		Code 3 Unpaid domestic services for household and family members		Code 4 Unpaid caregiving services for household and family members		Code 5 Unpaid volunteer, trainee and other unpaid and other work		Code 37 Shopping for own household and family members		Code 38 Travelling, moving or accompanying goods or persons	
Panel A: Both Major and Minor Activity												
$PM2.5\ (\mu g/m^3)$	0.011	0.021	0.011	0.020	-0.000	0.001	-0.001	0.000	0.008	0.023	0.007	0.017
	(0.004)**	(0.011)*	(0.004)***	(0.011)*	(0.000)	(0.001)	(0.003)	(0.007)	(0.004)**	(0.013)*	(0.003)**	(0.007)**
Adj. R2	0.094	-0.003	0.092	-0.003	0.015	-0.003	0.134	-0.002	0.095	-0.003	0.062	-0.003
Dep. Var. Mean	18.103	18.103	16.415	16.415	0.509	0.509	2.371	2.371	14.195	14.195	5.082	5.082
KP F-Statistic		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
Panel B: Only Major Activity												
$PM2.5\ (\mu g/m^3)$	0.010	0.015	0.011	0.017	-0.000	0.001	-0.001	-0.002	0.009	0.022	0.004	0.007
	(0.004)**	(0.011)	(0.004)***	(0.010)*	(0.000)	(0.001)	(0.003)	(0.006)	(0.004)**	(0.012)*	(0.002)**	(0.005)
Adj. R2	0.090	-0.003	0.088	-0.003	0.013	-0.003	0.130	-0.002	0.086	-0.002	0.057	-0.003
Dep. Var. Mean	17.811	17.811	16.055	16.055	0.470	0.470	2.267	2.267	12.552	12.552	4.341	4.341
KP F-Statistic		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

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each column observation corresponds to a unique surveyed household. The sample is restricted to respondents between 18 and 60 and those who report their gender as either male or female. The sample includes households that have at least one male and female member. The dependent variable in all columns is the ratio of time spent on outdoor activities in minutes in the respective activity code by male to female members of the households. Activities classified as outdoor are discussed in the main text. The column headings indicate which activity codes are used for time-use computation. Each specification in all columns includes 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 A17: Effect of Air Pollution on Time Spent Outdoors – Leisure Activities Male Share

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	Major Division 6-9 Leisure		Code 6 Learning		Code 7 Socializing and communication, community participation and religious practice		Code 8 Culture, leisure, mass media and sports practices		Code 9 Self-care and maintenance	
Panel A: Both Major and Minor Activity										
$PM2.5\ (\mu g/m^3)$	-0.007	-0.022	-0.002	-0.007	0.002	0.003	0.000	0.007	-0.006	-0.034
	(0.004)*	(0.013)*	(0.002)	(0.005)	(0.002)	(0.005)	(0.003)	(0.010)	(0.004)	(0.010)***
Adj. R2	0.083	0.009	0.023	0.003	0.086	-0.000	0.091	0.012	0.151	-0.006
Dep. Var. Mean	22.997	22.997	6.239	6.239	4.274	4.274	12.097	12.097	4.795	4.795
KP F-Statistic		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
Panel B: Only Major Activity										
$PM2.5\ (\mu g/m^3)$	-0.008	-0.026	-0.001	-0.007	0.001	0.001	-0.000	0.007	-0.006	-0.035
	(0.004)*	(0.013)**	(0.002)	(0.005)	(0.002)	(0.005)	(0.003)	(0.010)	(0.004)*	(0.010)***
Adj. R2	0.079	0.009	0.022	0.003	0.074	-0.001	0.089	0.012	0.148	-0.007
Dep. Var. Mean	21.992	21.992	6.153	6.153	3.782	3.782	11.577	11.577	4.410	4.410
KP F-Statistic		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

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each column observation corresponds to a unique surveyed household. The sample is restricted to respondents between 18 and 60 and those who report their gender as either male or female. The sample includes households that have at least one male and female member. The dependent variable in all columns is the ratio of time spent on outdoor activities in minutes in the respective activity code by male to female members of the households. Activities classified as outdoor are discussed in the main text. The column headings indicate which activity codes are used for time-use computation. Each specification in all columns includes 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 A18: 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 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, 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 A19: Effect of Air Pollution on Time Spent Outdoors – Alternate Outdoor Classification

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
	Baseline		Outdoor TUS		Relaxed Classification	
Panel A: Both Major and Minor Activity						
$PM2.5\ (\mu g/m^3)$	-0.028	-0.094	-0.013	-0.050	-0.020	-0.069
	(0.012)**	(0.034)***	(0.014)	(0.035)	(0.013)	(0.035)**
Adj. R2	0.357	0.321	0.573	0.558	0.384	0.356
Dep. Var. Mean	157.875	157.875	333.826	333.826	183.107	183.107
KP F-Statistic		16.711		16.711		16.711
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	-0.015	-0.055	-0.018	-0.058
	(0.012)**	(0.034)***	(0.014)	(0.035)	(0.013)	(0.034)*
Adj. R2	0.362	0.326	0.573	0.559	0.390	0.363
Dep. Var. Mean	162.057	162.057	334.743	334.743	188.395	188.395
KP F-Statistic		16.711		16.711		16.711
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 activity type. 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 A20: Effect of Air Pollution on Time Spent on Activities related to Health

	(1) OLS	(2) IV
Panel A: Both Major and Minor Activity		
$PM2.5\,(\mu g/m^3)$	0.001	0.003
	(0.001)	(0.004)
Adj. R2	0.011	0.003
Dep. Var. Mean	2.620	2.620
KP F-Statistic		16.711
N	314,125	314,125
Panel B: Only Major Activity		
$PM2.5\,(\mu g/m^3)$	0.001	0.003
	(0.001)	(0.005)
Adj. R2	0.011	0.003
Dep. Var. Mean	2.761	2.761
KP F-Statistic		16.711
N	314,125	314,125

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The dependent variable in all columns is the amount of time spent on health related activities in minutes. Activities classified as those related to health include the following three-digit activity codes: 135, 372, 412, 422, 431, 512, 941, 942, and 949. Each specification in all columns includes 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 A21: Effect of Air Pollution on Time Spent Outdoors – Robustness to Adding Industry Codes

	(1) OLS	(2) IV	(3) OLS	(4) IV
	Baseline		Add NIC 2008 Codes	
Panel A: Both Major and Minor Activity				
$PM2.5\ (\mu g/m^3)$	-0.028	-0.094	-0.052	-0.160
	(0.012)**	(0.034)***	(0.019)***	(0.055)***
Adj. R2	0.357	0.321	0.221	0.143
Dep. Var. Mean	157.875	157.875	235.269	235.269
KP F-Statistic		16.711		16.710
N	314,125	314,125	172,109	172,109
Panel B: Only Major Activity				
$PM2.5\ (\mu g/m^3)$	-0.028	-0.087	-0.051	-0.150
	(0.012)**	(0.034)***	(0.019)***	(0.056)***
Adj. R2	0.362	0.326	0.223	0.146
Dep. Var. Mean	162.057	162.057	243.290	243.290
KP F-Statistic		16.711		16.710
N	314,125	314,125	172,109	172,109

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique respondent in the surveyed household. The sample is restricted to respondents between the ages of 18 and 60 and those who report their gender to be either male or female. The dependent variable in all columns is the amount of time spent on outdoor activities in minutes. Activities classified as outdoor are discussed in the main text. The column header shows the specification type. Each specification in all columns includes 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.