Clearing the Air: How Pollution Shapes Labor Supply in Bangladesh

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Research on the impact of air pollution on labor supply, particularly in rural areas of developing countries, is considerably limited. This paper examines the impact of air pollution on hours worked in rural Bangladesh. Utilizing panel household survey and satellite data on pollution, this study employs an instrumental variable approach that exploits the exogenous occurrence of thermal inversions. A 10 $\mu g/m^3$ increase in $PM_{2.5}$ reduces monthly hours worked by 14.9% (16.4 hours per month) relative to the mean of 109.9 hours. The impact is concentrated among outdoor and agricultural workers although it does not differ significantly by gender or household income. Pollution increases the incidence of respiratory symptoms and the number of days of illness among workers, and men respond by working fewer days. Pollution has no effect on the morbidity of young children or the elderly, and women in households with such dependents do not reduce their hours more than other workers. The decline in labor supply therefore reflects deteriorating worker health rather than increased caregiving. Overall, these findings underscore the labor-market costs incurred in highly polluted, low-income settings where such effects remain understudied.

Keywords: pollution, hours worked, labor supply

JEL classifications: C36, Q53, J21

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1 Introduction

In recent years, air pollution has emerged as a pressing global environmental issue and a major threat to human health. Globally, nearly 99% of the population breathes air containing pollutants exceeding World Health Organization (WHO) recommended thresholds, contributing to nearly 6.7 million deaths annually (WHO 2024). In 2019 alone, pollution caused 4.2 million premature deaths, of which 89% occurred in low- and middle-income countries (LMICs) (WHO 2024). The situation is particularly worse in LMICs where rapid development and urbanization have rendered air unbreathable (Brooks et al. 2023; Jayachandran 2022; Dechezlepretre, Rivers and Stadler 2019).

Air pollution worsens health (Currie et al. 2014; Tanaka 2015), educational performance (Balakrishnan and Tsaneva 2021; Bedi et al. 2021; Bharadwaj et al. 2017; Ebenstein et al. 2016; Lavy, Ebenstein, and Roth 2014; Roth 2021; Zhang et al. 2018; Zivin et al. 2020), subjective well-being (Li et al. 2019, Zheng et al. 2019) and labor market productivity (Adhvaryu, Kala, and Nyshadham 2022; Chang et al. 2019; Chen and Zhang 2021; Li, Liu, and Salvo 2015; Zivin and Neidell 2012; Fu et al. 2017; He et al. 2019). Despite such growing evidence, much less is known about how pollution affects labor supply in rural areas where employment is often informal and physically intensive, thereby rendering labor markets more vulnerable to such environmental shocks. This paper therefore investigates the impact of pollution on rural labor supply in Bangladesh, the most polluted country in the world (Raza, Mahmud, and Rabie 2023). This research contributes to two strands of economic fields: labor and environment.

The Bangladeshi context is relevant to examine the relationship between air pollution and labor supply. Even though the country has witnessed sustained economic growth over the past two decades, it remains the world's most polluted country (Energy Policy Institute 2023) with 164.8 million people living in areas where average pollution levels exceed both the WHO guideline of 5 $\mu g/m^3$ and the national standard of 35 $\mu g/m^3$. Air pollution is the second greatest threat to human health in the country, with the economic cost of health issues

attributable to pollution ranging between US11.5−13 billion, or 3.9-4.4% of GDP in 2019 compared to past year (Raza, Mahmud, and Rabie 2023). These costs reflect productivity losses due to impaired health, reduced labor supply and the existence of pollution-based poverty traps, where high pollution levels exacerbate health, education and labor market outcomes (Fuller et al. 2022).

In Bangladesh, rural areas are more vulnerable to the adverse impact of pollution on labor markets. Households located in these areas are ill-equipped to buffer themselves against environmental shocks. The lack of adequate health infrastructure coupled with insufficient information on the health risks of pollution reduces the likelihood that individuals get treated on time (Balakrishnan and Tsaneva 2021). The problem is further compounded with workers in rural areas more likely to engage in physically demanding jobs such as manufacturing and agriculture, due to low education and limited technical skills (Huang et al. 2021). Moreover, the lower baseline health status common in developing and low-income countries exacerbates pollution impacts (Balakrishnan and Tsaneva 2021; Chen et al. 2013). In this setting, this paper fills an important gap, hypothesizing that pollution impacts are likely to be more severe in rural areas (Huang et al. 2021; Balakrishnan, Cohen and Smith 2014).

In this setting, it is important to measure the rural labor supply response to ambient pollution for both external validity and policy design. Prior literature on the labor supply effects of pollution is primarily available for urban or developed countries (Hanna and Oliva 2015; Aragon, Miranda and Oliva 2017) and is scarce for developing countries, let alone concentrated only in rural areas (Chan, Pelli, and Vienne 2023; Huang et al. 2021). Because households in rural areas operate close to subsistence and face incomplete credit and insurance markets, they are more likely to absorb income shocks than to smooth them. As nearly 60% of the country's population lives in rural areas and about 35% of employment is in agriculture (World Bank 2024), most workers in rural areas are primarily involved in manual, outdoor and physically intensive tasks and are therefore more exposed to pollution. As a result, applying national or urban estimates to this population yields a downward-biased

measure of the true burden borne by this population.

Availability and access to reliable pollution data is also a challenge. Nearly 25% of countries having the highest levels of pollution have sparsely located pollution monitors, mostly in urban areas, leaving rural areas unmeasured (Barwick et al. 2019; Fan and Grainger 2023; Balakrishnan et al. 2014; Balakrishnan and Tsaneva 2021). In Bangladesh, the Department of Environment uses Continuous Air Monitoring Station (CAMS) to collect real-time measurement of pollutants in only 8 major cities (Dhaka, Narayaganj, Ghazipur, Chittagong, Rajshahi, Khulna, Barisal and Sylhet) of the country. This problem is further compounded in instances where local officials strategically avoid pollution hotspots when placing monitors (Grainger and Schreiber 2019), increasing pollution emissions during non-monitoring periods (Zou 2021) or manipulate data to report lower pollution levels (Gu, Bian, and Elahi 2020). To counter these problems, I utilize satellite data instead (Jayachandran 2009). I utilize pollution data from Atmospheric Composition Analysis Group (ACAG) at Washington University in St. Louis (van Donkelaar et al. 2021), which provides monthly pollution levels at a spatial resolution of 1 km. Using household coordinates, I match each household to the pollution grid cell and merge them with BIHS survey data.

The identification in this paper relies on variation in pollution over time and across households in Bangladesh. As pollution is not randomly assigned across space or time, it is difficult to establish a causal link between pollution and labor supply. Potential sources of endogeneity include residential sorting, reverse causality and environmental confounding- the possibility that pollution co-varies with weather and other environmental conditions that independently affect labor supply (Freeman et al. 2019; Khanna et al. 2021; Zivin and Neidell 2013; Aguilar-Gomez et al. 2022). Conditional on weather controls, thermal inversions, when a mass of cold air gets caught below a mass of hot air, trapping pollutants and degrading air quality, provide a plausibly exogenous source of variation in pollution, making them a suitable instrumental variable to address these concerns.

The identifying assumption of my instrument is that, conditional on household fixed

effects, season by year fixed effects, weather and household controls, changes in thermal inversions are unrelated to changes in labor outcomes except through their impact on air pollution. My first stage estimates show that there is a positive and statistically significant relationship between thermal inversions and air pollution, with a one standard deviation increase in thermal inversions increasing PM2.5 concentrations by 2 $\mu g/m^3$ (2.1%). My baseline results indicate that a 10 $\mu g/m^3$ increase in PM2.5 leads to a reduction of about 16.4 hours (14.9%) worked by rural workers per month.

I then examine two potential mechanisms: workers' own health and caregiving for sick dependents. I find that a 10 $\mu g/m^3$ increase in PM2.5 raises the probability of reporting any illness by 12.6 percentage points, a persistent cough by 5 percentage points, and of any respiratory symptom by 5.5 percentage points and increases the share of days on which workers are ill by 8.4 percentage points, while a placebo outcome that should not respond to air pollution, diarrhea, does not change. While men respond to this health burden by working lesser number of days, women continue to work. On the other hand, I do not find any evidence for the caregiving channel. Pollution does not affect the illness of young children or elderly household members, and the labor supply response also does not differ between households with and without such dependents, and women in these households do not reduce their hours more than other workers. Taken together, these results indicate that pollution reduces labor supply by impairing workers' own health rather than by increasing the demand for care within the household. My results are consistent across alternative specifications. In particular, my robustness checks include using an alternative instrument, controlling flexibly for weather and when I allow for trends in hours within survey seasons. I also test for attrition and migration. My estimates remain unchanged in both cases. Lastly, I conduct two placebo tests, one using future inversions and one where I randomly assign inversions across locations. Results from these tests also yield small and statistically insignificant estimates. Across all specifications, my estimates remain robust and consistent.

This paper contributes to the existing literature on air pollution and labor markets in

three main ways. First, it contributes to the quasi-experimental literature on the impact of air pollution on rural labor supply. Most of the existing studies focus on determining countrywide or urban labor supply responses or productivity outcomes, with little focus on rural areas in developing countries (Carson, Koundouri, and Nauges 2011). I also utilize high resolution satellite data on pollution and thermal inversions which allows me to overcome sparse coverage, urban bias and potential manipulation concerns associated with developing country ground-based monitoring data. Second, I utilize household panel data with a comprehensive set of weather and demographic controls and a rich fixed effects structure to address unobserved time invariant and time varying factors that could affect both air pollution and labor supply. Leveraging thermal inversions as an exogenous source of variation in pollution allows me to address key identification concerns discussed earlier and yield credible causal estimates. Third, I provide direct evidence on the mechanism. Whereas studies from urban and middle-income settings emphasize caregiving (Aragón, Miranda and Oliva 2017; Kim, Manley and Radoias 2017; Han et al. 2023), I show that in rural Bangladesh, the effect operates through workers' own health, which deteriorates for men and women alike, rather than through caregiving, even among women in households with young children or elderly members.

The remainder of the paper is organized as follows: Section 2 provides a brief background on air pollution and its impact on health and labor supply. Section 3 describes the data sources and presents the descriptive statistics. Section 4 provides the empirical framework, explains the identification strategy and presents the main instrumental variable results, followed by the heterogeneity analysis, the mechanisms and the robustness checks. Section 5 concludes the paper.

2 Context

2.1 Air Pollution in Bangladesh

Considered as the most polluted country in the world, Bangladesh has 164.8 million people residing in areas where the particulate pollution exceeds the country's national standard of 35 µg/m^3 (Energy Policy Institute 2023). The country's residents are expected to gain 6.7 years in life expectancy if this guideline is met. In 2019, air pollution was considered to have led to 78000-88000 deaths and 1 billion days lived with illnesses in the country (Raza, Mahmud, and Rabie 2023). In terms of economic losses, air pollution led to a fall in GDP by 3.9-4.4% in 2019 (Raza, Mahmud, and Rabie 2023). The major sources of air pollution include vehicular emissions, coal-fired power plants, brick kilns, construction activities and biomass burning.

By 2023, the country's annual average PM2.5 concentration was 79.9 µg/m^3, more than twice the national standard set in 2022 (35 µg/m^3) and 15 times the WHO's guideline of 5 µg/m^3. If the PM2.5 concentrations were reduced to meet the national standard, 19% deaths, 21% Years of Life Lost (YLL) and 12% Years Lived with Disability (YLD) could be averted (Nesan and Kelly 2025). In 2023 alone, pollution was responsible for 102,456 deaths from ischemic heart disease, stroke, chronic obstructive pulmonary disease, lower respiratory infections and lung cancer (Nesan and Kelly 2025). High pollution also led to significant morbidity with 670, 000 annual emergency room visits due to asthma and 262 million lost workdays annually.

Among particulate matter, PM2.5 is considered to be more detrimental to health than other coarser particulate matter (Hoffmann and Rud 2024). Consisting of tiny particles having a mean aerodynamic diameter of up to 2.5μm, PM2.5 can remain airborne from a few days to weeks and penetrate deep into the lungs and impair respiratory function (Aguilar-Gomez et al. 2022; Chay et al. 2003; Isen et al. 2017). It is emitted by natural sources such as volcanoes and wildfires or anthropogenic sources such as industrial activities, combustion

of fossil fuels including biomass burning and chemical reactions of air emissions (Yamada and Narita 2025).

2.2 Air Pollution and Health Outcomes

Exposure to air pollution can lead to both mild and life-threatening health issues. Mild impacts include changes in blood pressure, headaches, and irritation of the eyes, ear, nose, throat, skin and lungs (Auchincloss et al. 2008; Pope 2000; Ghio, Kim and Devlin 2000; Zhou and Zhang 2023). Pollution is also associated with reduced blood flow and cell oxygenation, leading to chest pain and tightness, fatigue, irritability, and impatience (Huang et al. 2021). This further impairs attention, productivity and cognitive function, thereby affecting a range of behavioral and socioeconomic outcomes (Aguilar-Gomez et al. 2022).

Furthermore, air pollution has also been linked to chronic illnesses such as diabetes, autism, neurological disorders, and weakened neonatal immune system (Pearson et al. 2010; Morales-Suarez-Varela, Peraita-Costa, and Llopis-Gonzalez 2017; Han et al. 2023). It has also been associated with changing emotional states and causing anxiety and depression (Fonken et al. 2011). Pollution can also lead to cardiovascular and respiratory impairment including chronic coughs, shortness of breath and asthma attacks (Zhang, Hao and Lu 2018; Han et al. 2023). Particulate matter can also penetrate the bloodstream and cause cardiovascular complications such as stroke and heart failure, leading to increased hospitalizations and mortality rates (Bell et al. 2004; Brook et al. 2010; Hoffmann and Rud 2024; Ranft et al. 2009; Genc et al. 2012).

2.3 Air Pollution and Labor Supply

There is a sizable body of evidence focusing on determining the impact of pollution on labor supply responses. Exposure to pollutants has a detrimental impact on workers' labor market outcomes in two main ways. First, it reduces workers' functionality to work, also known as 'presenteeism' and health problems arising from pollution can interfere with work-

ers' daily routines (Chang et al. 2016; Han et al. 2023; Kamble 2024). Second, it can lead to absenteeism with workers missing work or reducing hours worked due to their own illness or to provide caregiving to sick household members (Chang et al. 2016; Hanna and Oliva 2015; Han et al. 2023; Yamada and Narita 2025; Kögel 2023). Studies have found that households having susceptible members including children and the elderly face more detrimental consequences of pollution (Aragon, Miranda, and Oliva 2017; Li and Li 2022). Intra-household heterogeneity reveals mothers reducing their hours worked while fathers' labor supply remains unchanged as the former take on traditional caregiving roles (Han et al. 2023).

Prior literature focuses both on the extensive margin of labor supply, with pollution leading to reduced labor supply due to its impact on health (Kim, Manley and Radoias 2017) and on the intensive margin, with pollution leading to reduced productivity (Zivin and Neidell 2012; Chang et al. 2016; Archsmith, Heyes and Saberian 2018; Chang et al. 2019; He, Liu and Salvo 2019; Kahn and Li 2020). This includes papers investigating detrimental impact of PM2.5 on hours worked in developing countries (Aragon, Miranda, and Oliva 2017; Hanna and Oliva 2015; Zhang et al. 2018).

In some instances, the relationship between pollution and labor supply is not linear, with research finding a positive relationship between PM2.5 exposure and hours worked upto a threshold beyond which the trend reverses (Zhang, Chen, and Zhang 2018). Furthermore, there is limited evidence on the impact of pollution on labor supply in rural areas (Chan, Pelli, and Vienne 2023). Research also finds that effective legislation can help reduce pollution levels and improve labor supply (Hanna and Oliva 2015; Viard and Fu 2015).

3 Data and Descriptive Statistics

This section outlines the data utilized in this paper. I gather information from multiple data sources to conduct the analysis. Data on labor supply is obtained from Bangladesh Integrated

Household Survey (BIHS) 2011-12, 2015 and 2018-19 while pollution data is sourced from Atmospheric Composition Analysis Group (ACAG) at Washington University in St. Louis (van Donkelaar et al. 2021). Data for thermal inversions and weather is acquired from ECMWF ERA5 reanalysis data.

3.1 Bangladesh Integrated Household Survey

Conducted by International Food Policy Research Institute (IFPRI), Bangladesh Integrated Household Survey (BIHS) is the most comprehensive, nationally representative individual level rural panel survey in the country. It covers detailed information on 6500 households in 325 primary sampling units regarding key socio-economic indicators including demographic characteristics, education, employment, anthropometric measurements, agricultural production, time allocation and women's empowerment. Figure 1 plots the location of Department of Environment ground based air monitoring stations (red triangles) and households (blue dots) included in the sample. The sample is nationally representative of rural areas with households being dispersed across the entire country. On the other hand, the ground monitors are sparsely located and concentrated in a few cities. Because of this, I utilize high resolution satellite pollution data providing complete and consistent spatial coverage to answer my research question.

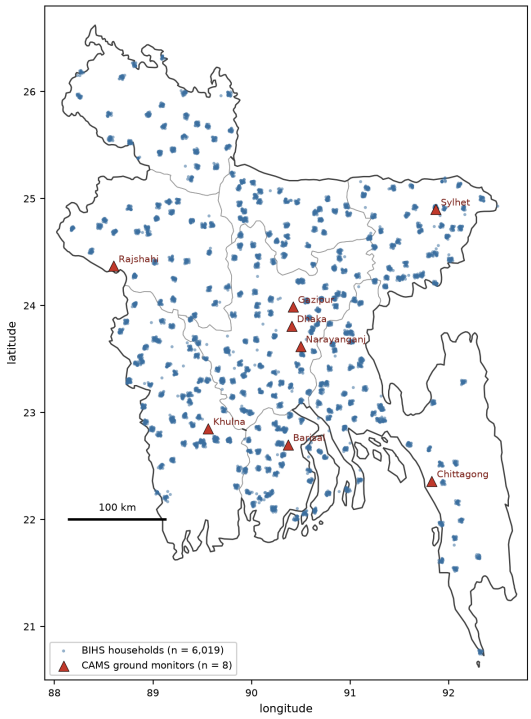


Figure 1: BIHS Household Sample and Ground-Monitor Coverage

Note: The map plots the 5,877 BIHS working-sample households (blue) — individuals aged 15–64 with a primary work activity and complete controls, across the three survey waves (2011–12, 2015, 2018–19) — together with the eight Department of Environment Continuous Air Monitoring Stations (CAMS; red triangles) in Dhaka, Narayanganj, Gazipur, Chittagong, Rajshahi, Khulna, Barisal, and Sylhet. The household sample covers rural areas nationwide, whereas the ground-monitoring network is sparse and concentrated in a few cities — motivating the use of the fine-resolution satellite (ACAG) pollution data. Division boundaries are shown in grey.

The primary variable of interest is the number of hours worked per month. The survey records employment information on all types of economic work performed by each household member aged 6 years and above in the week preceding the interview. This is the reference period week t. I restrict the sample to working individuals lying in the age range 15-64 years. Each respondent is required to report all economic activities that they are involved in. In cases where more than one activity is reported, I consider the activity with the highest number of hours worked reported as the primary one. 55% of workers in my sample report working in a single activity and primary activity accounts for 86% of total weekly hours on average. This shows primary activity hours closely track total hours worked by workers. Focusing on the primary activity only allows me to avoid measurement error introduced by

secondary jobs which tend to be sporadic and seasonal in nature and are reported with more noise. I scale weekly hours to calculate monthly hours worked. To exclude the influence of outliers, I trim the top 1% of my sample from the monthly hours distribution.

3.2 Pollution Data

I obtain satellite-based pollution data from Atmospheric Composition Analysis Group at Washington University in St. Louis (version V5.GL.05.02) (van Donkelaar et al. 2021). This provides information on monthly mean pollution for each 0.01°x0.01° grid (1 km at the equator) across the globe. Using household coordinates, I match every household to the pollution grid cell in which it is located and assign it the pollution level for that cell. I calculate average monthly pollution for each household in the sample for the month before working hours are realized. This is because pollution exposure affects labor supply with a delay rather than contemporaneously. Pollution operates through respiratory and cardiovascular morbidity and through caregiving for ill household members (Aragon, Miranda and Oliva 2017; Hanna and Oliva 2015), and neither channel produces an immediate labor supply response.

Figure 2 shows the spatial distribution of average monthly pollution levels across the 3 Bangladesh Integrated Household Survey (BIHS) waves (Wave 1: Sept 2011-March 2012, Wave 2: Dec 2014-Aug 2015, Wave 3: Oct 2018-Apr 2019) using Atmospheric Composition Analysis Group data. Pollution values mostly range between 50-120 µg/m^3, far above the national standard set in 2022 of 35 µg/m^3 and more than 20 times the WHO's guideline of 5 µg/m^3. This highlights the severity of pollution and its persistence in the country over the years. During the first wave, pollution is mostly concentrated in the southwestern and central regions of the country. However, it reduces considerably by 2015 although increased PM2.5 concentrations are present in the southwestern regions. In the last wave, pollution resurges, with the highest increases again experienced in the southwestern regions and moderate increases observed in the central regions of the country.

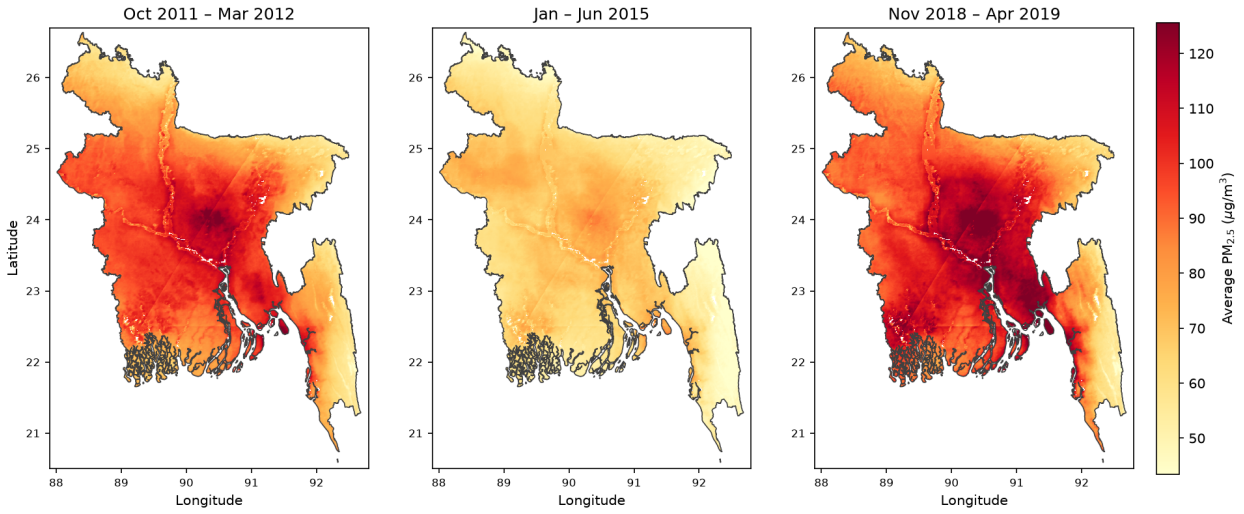


Figure 2: Average PM2.5 in Bangladesh (2011–2019)

Note: Average $PM_{2.5}$ over each survey window — Oct 2011–Mar 2012, Jan–Jun 2015, and Nov 2018–Apr 2019 — from the ACAG satellite grids (0.01°; van Donkelaar et al. 2021).

Figure 3 represents the trends in average monthly pollution in Bangladesh over the years 2011-2020. The figure represents the seasonality of PM2.5 levels across the year, with strong peaks reached during the dry winter months (October-March) and significant declines during the monsoon season (June-August). Because of this, I include season by year fixed effects in my main regression to account for seasonal variation in pollution.

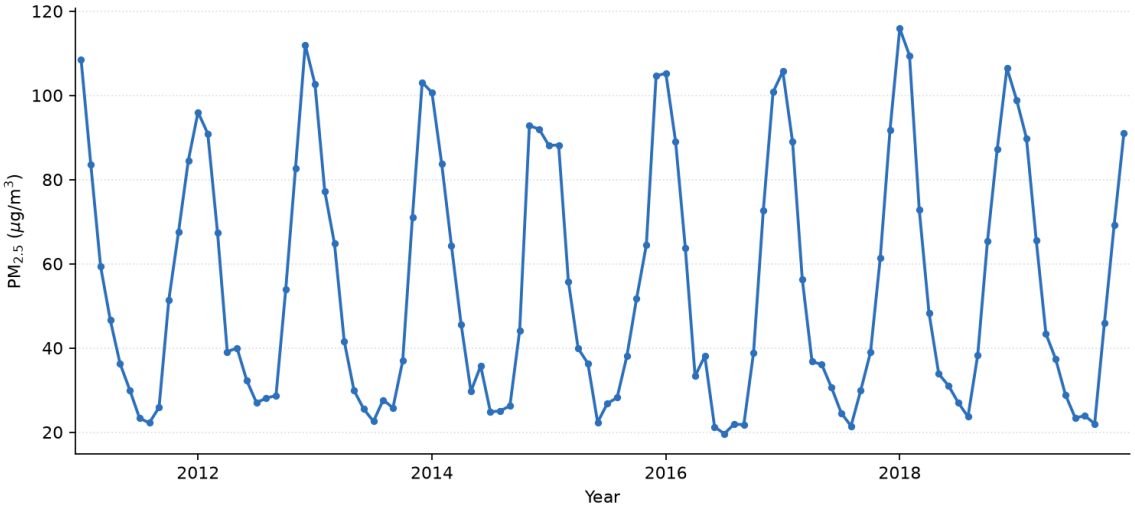


Figure 3: Monthly Average PM2.5 in Bangladesh, 2011–2019

Note: Monthly mean $PM_{2.5}$ averaged over Bangladesh, from the ACAG satellite grids (van Donkelaar et al. 2021). Pollution exhibits a pronounced seasonal cycle, peaking in the dry winter months and falling sharply during the monsoon (June–September), motivating the inclusion of season-by-year fixed effects.

3.3 Thermal Inversion Data

With altitude, temperature decreases, with the air becoming colder at higher altitudes. However, a thermal inversion occurs when the reverse happens, that is, when temperature increases with an increase in altitude. In other words, a mass of cold air gets trapped below hot air due to its higher density, and traps pollutants beneath it (Arceo, Hanna, and Oliva 2016; Ye, Huang and Chen 2023; Zhou and Zhang 2023; Chan, Pelli and Vienne 2023). These contribute to increased pollution including particulate matter (Arceo et al. 2016). Prior research also finds that severe thermal inversions are linked to some of the worst pollution events reported in history (Balakrishnan and Tsaneva 2021; Bailey et al. 2011; Malek et al. 2006).

I utilize European Center for Medium-Range Weather Forecasts (ECMWF) atmospheric reanalysis (ERA5) data to build the measure of thermal inversions. Produced by ECMWF, this dataset provides the latest version of global atmospheric reanalysis across 37 pressure layers. This data is collected hourly and has a spatial resolution of 0.25°x 0.25° (31x31

km). I define the occurrence of a thermal inversion when the temperature in the lower layer closest to the ground (1000hPa-110m) is lower than that in the upper layer (925hPa-760m) (Ye, Huang, and Chen 2023). I determine the average number of thermal inversions for each month at the household level. As a robustness check, I construct an alternative measure of inversions, inversion strength, which is determined by taking the temperature difference between the 1000hPa and the 925hPa layers. This helps capture the magnitude of the inversions.

Figure 4 plots total monthly thermal inversions from 2011-20. Inversions exhibit strong seasonality, with higher number of inversions being experienced in dry winter months (October-March) ranging between 35-55 inversion counts per month. During the monsoon season, they fall to near zero counts. Together, the series highlights the temporal variation of thermal inversions across the years.

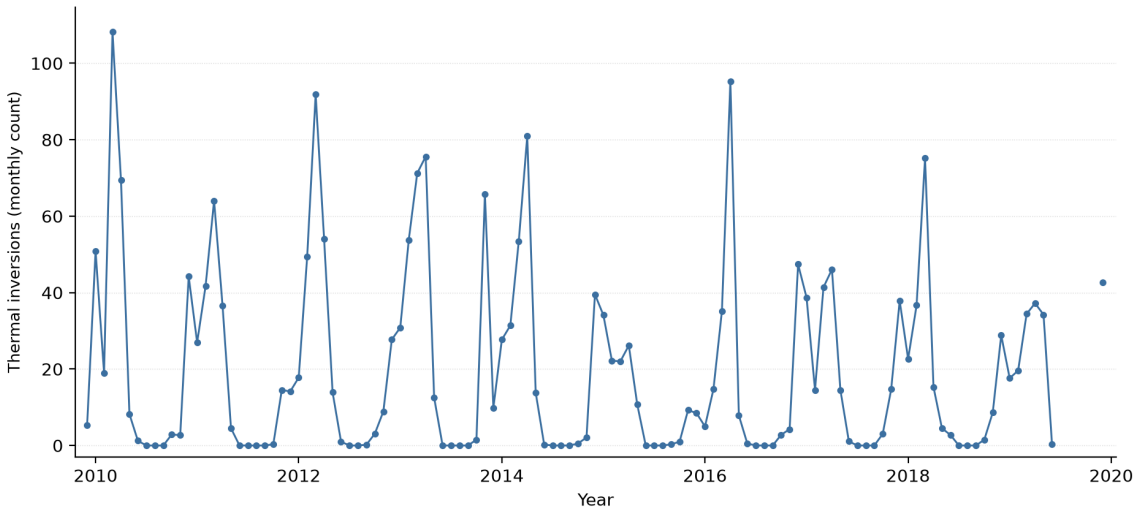


Figure 4: Monthly Thermal Inversions in Bangladesh, 2011–2019

Note: Monthly count of 925–1000 hPa (inv4-1) thermal inversions averaged over Bangladesh, from ERA5-hourly temperature levels. Inversions exhibit strong seasonality, peaking in the dry winter and pre-monsoon months and falling to near zero during the monsoon — the same seasonal pattern as $PM_{2.5}$ (Figure 3), consistent with thermal inversions trapping pollution near the surface.

Figure 5 maps the monthly number of thermal inversions across the 3 BIHS survey waves. Across most of the country, the frequency of inversions is fairly even and range between 0-40 inversions per month. Higher inversions are experienced in the southeastern parts of

Bangladesh.

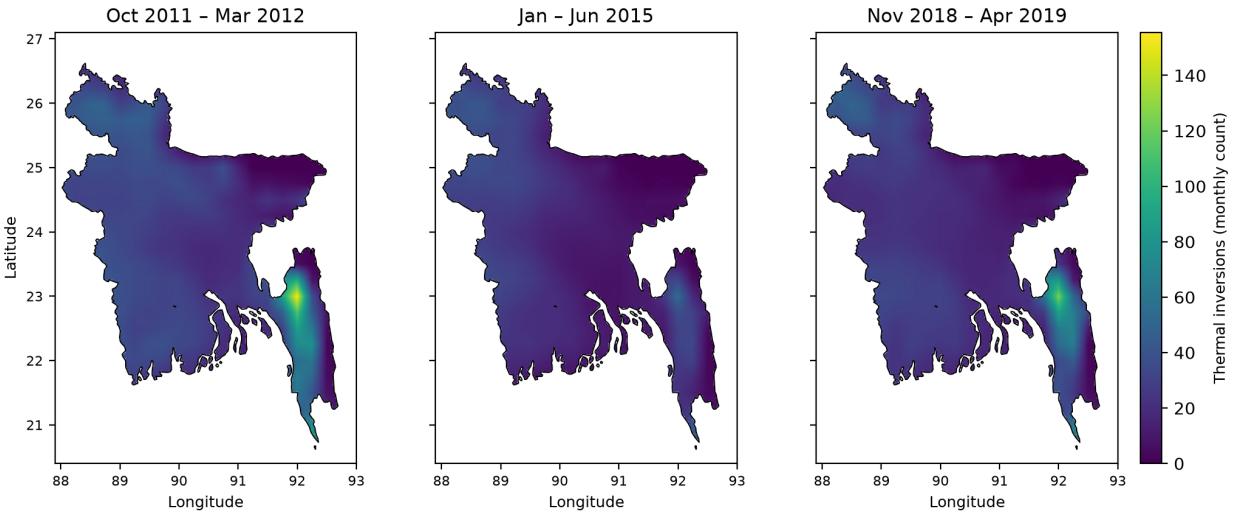


Figure 5: Average Thermal Inversions in Bangladesh (2011–2019)

Note: Average monthly count of 925–1000 hPa (inv4-1) thermal inversions over each survey window — Oct 2011–Mar 2012, Jan–Jun 2015, and Nov 2018–Apr 2019 — from ERA5 hourly temperature levels. An inversion occurs when the 925 hPa temperature exceeds the 1000 hPa temperature. Inversions are most frequent in the south-eastern hills; the scale is common across panels.

3.4 Weather Data

Information pertaining to weather controls affecting both air quality and workers' labor supply including wind speed, relative humidity, surface pressure, temperature and precipitation is taken from European Center for Medium-Range Weather Forecasts (ECMWF) Copernicus Climate Change Service (C3S) ERA5 reanalysis data. This provides information at a high spatial resolution of 0.25°x0.25° grid (31x31 km). I aggregate hourly data to determine monthly averages at the household level in the data.

Thermal inversions arise due to specific atmospheric conditions and may be closely associated with meteorological factors such as temperature and precipitation which also have an impact on human activities. To account for potential confounding arising from seasonal weather patterns, I control for these variables (Arceo, Hanna, and Oliva 2016; Chen et al. 2017; Deschenes and Greenstone 2007; Ye, Huang and Chen 2023). This allows me to isolate the effect of thermal inversions on pollution from broader meteorological factors, alleviating

any concerns regarding the exclusion restriction.

Table 1 represents the temporal distribution of the data used in this paper. I used all 3 rounds of Bangladesh Integrated Household Survey (BIHS). This first round includes data from households interviewed at the end of 2011 and the beginning of 2012 while the second round includes observations from the first two quarters of 2015. For the third round, responses are collected from the last quarter of 2018 and the first two quarters of 2019.

Table 1: Temporal Distribution of Data

	Year					
Quarter	2011	2012	2015	2018	2019	Total
Quarter 1 (Jan–Mar)	0	5,694	6,221	0	7,371	19,286
Quarter 2 (Apr–Jun)	0	0	5,655	0	1,260	6,915
Quarter 3 (Jul–Sep)	0	0	4	0	0	4
Quarter 4 (Oct–Dec)	5,420	0	0	1,315	0	6,735
Total	5,420	5,694	11,880	1,315	8,631	32,940

Table 2 presents descriptive statistics by wave for all variables used in the analysis. The estimation sample consists of 32,940 observations of 16,103 working individuals aged 15–64 in 5,877 households, of which 70% are observed in all three waves, 27% in two waves and 3% in one wave. Across waves, hours worked range between 103 and 116 per month, and the average age of working individuals is 36–37 years. Average household size varies between 4.5 and 4.9 members, and nearly 80% of the sample is married in each wave. Average pollution levels rise from 68.6 $\mu g/m^3$ in 2011–12 to 103.1 $\mu g/m^3$ in 2015 and 112.2 $\mu g/m^3$ in 2018–19. The average frequency of thermal inversions ranges between 0 and 128 per month. Weather conditions, including rainfall, wind speed, air pressure, relative humidity and temperature, exhibit some variation but remain fairly stable across rounds.

Table 2: Descriptive Statistics by Survey Wave

	2011–12					2015					2018–19				
Variable	Obs	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max
Panel A: Working Hours															
Monthly Hours	11,114	116.201	92.948	2.167	364.000	11,880	109.444	94.720	0.433	364.000	9,946	103.292	94.235	0.433	364.000
Log Monthly Hours	11,114	4.324	1.040	0.773	5.897	11,880	4.219	1.081	−0.836	5.897	9,946	4.111	1.138	−0.836	5.897
Panel B: Demographics and Work															
Age	11,114	36.262	12.219	15.000	64.000	11,880	37.339	12.739	15.000	64.000	9,946	37.154	13.052	15.000	64.000
Education	11,114	3.774	3.893	0.000	16.000	11,880	4.106	3.976	0.000	16.000	9,946	4.608	4.146	0.000	16.000
Household Size	11,114	4.530	1.622	1.000	15.000	11,880	4.829	1.841	1.000	20.000	9,946	4.895	1.952	1.000	19.000
Married	11,114	0.828	0.378	0.000	1.000	11,880	0.813	0.390	0.000	1.000	9,946	0.785	0.411	0.000	1.000
Male	11,114	0.530	0.499	0.000	1.000	11,880	0.503	0.500	0.000	1.000	9,946	0.485	0.500	0.000	1.000
Occupation															
Farming	11,114	0.598	0.490	0.000	1.000	11,880	0.604	0.489	0.000	1.000	9,939	0.609	0.488	0.000	1.000
Wage labor	11,114	0.158	0.365	0.000	1.000	11,880	0.143	0.350	0.000	1.000	9,939	0.120	0.325	0.000	1.000
Salaried	11,114	0.045	0.208	0.000	1.000	11,880	0.053	0.223	0.000	1.000	9,939	0.058	0.234	0.000	1.000
Business (self-emp/trader)	11,114	0.184	0.388	0.000	1.000	11,880	0.186	0.389	0.000	1.000	9,939	0.202	0.402	0.000	1.000
Other (prod./livestock)	11,114	0.014	0.117	0.000	1.000	11,880	0.015	0.122	0.000	1.000	9,939	0.011	0.102	0.000	1.000
Work location															
Outdoor	11,114	0.802	0.399	0.000	1.000	11,880	0.788	0.409	0.000	1.000	9,946	0.786	0.410	0.000	1.000
Income tercile															
Low	11,114	0.214	0.410	0.000	1.000	11,880	0.225	0.417	0.000	1.000	9,946	0.160	0.367	0.000	1.000
Middle	11,114	0.357	0.479	0.000	1.000	11,880	0.352	0.478	0.000	1.000	9,946	0.374	0.484	0.000	1.000
High	11,114	0.428	0.495	0.000	1.000	11,880	0.423	0.494	0.000	1.000	9,946	0.465	0.499	0.000	1.000
Panel C: Pollution, Thermal Inversions and Weather															
PM2.5 (μg/m^3)	11,114	68.559	28.439	19.800	158.200	11,880	103.127	29.854	23.100	203.000	9,946	112.160	31.512	41.400	225.300
Thermal Inversions (hours/month)	11,114	5.137	10.099	0.000	104.000	11,880	22.469	17.891	0.000	128.000	9,946	13.349	16.733	0.000	98.000
Precipitation (mm)	11,114	94.841	154.896	0.131	720.832	11,880	29.673	67.506	0.001	796.182	9,946	37.645	62.071	0.006	466.090
Temperature (°C)	11,114	24.299	4.013	14.535	28.948	11,880	20.615	2.625	14.655	28.375	9,946	20.784	3.299	14.504	29.556
Wind Speed (m/s)	11,114	1.872	0.687	0.859	5.105	11,880	1.966	0.332	1.017	5.103	9,946	1.898	0.409	0.789	4.047
Air Pressure (hPa)	11,114	1007.390	7.018	933.440	1013.696	11,880	1011.886	6.144	937.011	1016.203	9,946	1011.575	7.309	937.942	1017.979
Relative Humidity (%)	11,114	80.933	3.750	68.881	89.583	11,880	77.133	5.464	60.518	86.332	9,946	75.356	4.400	65.511	85.653

Notes: Estimation sample of workers aged 15–64 with a primary work activity (top-1%-trimmed monthly hours) in households observed in at least two survey waves; N = 32,940 (11,114 in 2011–12; 11,880 in 2015; 9,946 in 2018–19). Outdoor work comprises agricultural day labor, earth work, tea-garden and construction labor, mason/rod-welder, own-farm (crop) work, sharecropper/tenant and homestead farming, fishing and fish-pond work, sweeper, scavenger, transport helper, rickshaw/van pulling, motor-vehicle driver, porter, poultry, livestock and dairy raising, cobbler, clothes washer, vehicle mechanic, beggar, roadside small trader, fish trader, milk collector, animal breeder and veterinary/paravet work; factory, salaried/office and enclosed shop and craft occupations are classified as indoor. Thermal inversions are the share of hours in the month in which the temperature at 925 hPa exceeds the temperature at 1000 hPa (ERA5).

3.5 Statistical Challenges and Identification Strategy

Because pollution is not randomly assigned across space or time, it is difficult to determine the causal effect of pollution on hours worked. One concern is simultaneity where economic activities are correlated with both PM2.5 and hours worked (Yamada and Narita 2025). Areas with higher labor force participation and industrial activities experience higher pollution, thereby leading to a positive correlation between pollution and labor supply. Second, residential sorting can bias estimates, with individuals choosing where to live based on several factors including employment opportunities and local amenities available in that area (Freeman et al. 2019; Khanna et al. 2021; Zivin and Neidell 2013; Aguilar-Gomez et al. 2022; Mink 2025). Higher income households or more health-conscious workers will "vote with their feet" and sort into locations having better air quality (Chen, Oliva, and Zhang 2024; Freeman et al. 2019; Gu, Bian, and Elahi 2020; Ito and Zhang 2020). Conversely, cities serve as hubs for highly skilled workers due to better employment opportunities, yet these areas are also a major source of pollution (Zivin and Neidell 2013). However, such areas may also have better access to healthcare, which could circumvent some of the adverse effects of pollution. As a result, the direction of bias arising from endogeneity remains ambiguous.

Third, selection bias can introduce bias with workers adjusting their labor supply according to air quality deterioration (Ye, Huang and Chen 2023). They may adopt avoidance behaviors including working less hours or working less efficiently or take up caregiving responsibilities when household members fall ill or avail medical insurance (Ye, Huang and Chen 2023). Measurement error also poses a serious challenge and can bias OLS estimates (Chan, Pelli, and Vienne 2023). Pollution monitors, especially in developing countries, are sparsely located and their distance from survey sites introduces measurement error in data which is difficult to account for (Ye, Huang, and Chen 2023). Compared to developed countries where the monitor density is much higher (US-3.4 monitors/million people), developing countries such as Bangladesh (0.07 monitors/million people) and India (0.14 monitors/million people) have a scarcity of ground-level monitors (Brauer et al. 2019). Local data manipulation and

misreporting pollution levels may also lead to inaccurate results (Gu, Bian and Elahi 2020).

To address these endogeneity concerns, I employ the instrumental variable (IV) method and exploit the meteorological phenomenon of thermal inversions. This occurs when a mass of cold air gets caught below a mass of hot air, trapping pollutants and degrading air quality (Arceo, Hanna, and Oliva 2016). Controlling for weather variables likely to influence working hours, the occurrence of thermal inversions appears to be as good as randomly assigned and independent of economic activities. Because of being random, they are unlikely to be related to socioeconomic conditions and therefore satisfy the exclusion restriction condition for an instrumental variable. Furthermore, I argue that thermal inversions affect labor supply solely through the channel of changing air quality levels.

Thermal inversions have been widely used as an instrumental variable for pollution in the environmental economics literature (Arceo, Hanna, and Oliva 2016; Balakrishnan and Tsaneva 2021; Chen et al. 2021; Jans et al. 2018; Sager 2019; Dechezlepretre, Rivers, and Stadler 2019; Fu et al. 2021; Ye, Huang, and Chen 2023; Molina 2021; Deschenes et al. 2020; Mink 2025). Other papers have used different instruments for pollution including inversion strength (Arceo, Hanna, and Oliva 2016; Chen, Oliva and Zhang 2024) changes in local wind direction (Han et al. 2023), maximum wind speed (Gu et al. 2019; Gu, Bian and Elahi 2020; Li and Zhang 2019; Kögel 2023), planetary boundary layer height (Mink 2025), temperature and precipitation (Kamble 2024), ventilation index (Broner, Bustos, and Carvalho 2012; He et al. 2019) and daily airplane taxi time (Schlenker and Walker 2016).

I use monthly thermal inversions as an instrument for two reasons. First, with labor supply as my outcome, the exclusion restriction holds only if it does not impact labor supply through channels other than pollution. Other instruments such as temperature and precipitation have a direct impact on hours worked. Inversions, on the other hand, are a configuration of the upper atmosphere that workers do not observe. Because of this, inversions can plausibly shift labor supply only through air quality, conditional on weather controls. Unlike other instruments such as wind direction, ventilation index and airport taxi

time which require a known source of emission, inversions do not require a known pollution source and can be measured for every household in my sample.

4 Empirical Analysis

I adopt an instrumental variable two stage least squares approach to determine the causal impact of pollution exposure on hours worked using thermal inversions as a source of exogenous variation in pollution levels as below:

$$\text{PM2.5}_{g,t-1} = \alpha_0 + \alpha_1 \text{Thermal Inversions}_{g,t-1} + \alpha_2 X_{i,t} + \alpha_3 W_{g,t-1} + \rho_h + \gamma_{s,y} + \varepsilon_{i,t} \quad (1)$$

$$\log(\text{Hours}_{i,t}) = \beta_0 + \beta_1 \widehat{\text{PM2.5}}_{g,t-1} + \beta_2 X_{i,t} + \beta_3 W_{g,t-1} + \tau_h + \delta_{s,y} + \vartheta_{i,t} \quad (2)$$

where $\log(\text{Hours}_{i,t})$ denotes hours worked by individual i (in household h) in the reference month t. $\text{PM2.5}_{g,t-1}$ denotes the average monthly concentration of fine particulate matter ($\text{PM}_{2.5}$) in pollution grid cell g in month $t-1$, that is, at a one-month lag relative to the labor reference period. $\text{Thermal Inversions}_{g,t-1}$ denotes the corresponding count of thermal inversions in cell g in the same lagged month $t-1$, so that pollution and its instrument are both measured one month before labor outcomes are observed. $X_{i,t}$ represents individual and household controls including age, education, household size and marital status. $W_{g,t-1}$ represent one-month-lag monthly weather controls including temperature, precipitation, wind speed, air pressure, and relative humidity. ρ_h and τ_h represent household fixed effects that absorb time-invariant characteristics of each household including its location, wealth and baseline health. $\gamma_{s,y}$ and $\delta_{s,y}$ represent season-by-year fixed effects—where s indexes the season and y the survey year (2011, 2012, 2015, 2018, and 2019)—that absorb season-specific shocks to pollution and labor supply within each wave, common to all areas. Standard errors are clustered at the thermal-inversion grid level g.

Equation 1 represents the first stage estimation where the coefficient of interest is α_1. This represents the change in pollution levels attributable to a change in thermal inversions.

Equation 2 represents the second stage regression where β_1 captures the impact on labor supply of change in monthly hours worked.

Table 3 reports results from IV FE regression. Column 1 reports the first stage relationship between pollution and thermal inversions. This is positive and statistically significant, with a one standard deviation increase in thermal inversions being associated with a 2 µg/m^3 increase in PM2.5 concentrations, corresponding to approximately 2.1% of mean pollution levels (94.2 µg/m^3). The Kleibergen-Paap F statistic from the first stage regression is 81.7, greater than the Stock-Yogo 10% maximal IV size critical value of 16.38 (Stock and Yogo 2005).

Column (2) reports the second-stage IV estimates. The estimated effect of pollution on hours worked is negative and statistically significant at the 1% level. The point estimate implies that a 10 µg/m^3 increase in PM2.5 is associated with a 14.9% reduction in monthly hours worked, a loss of roughly 16.4 hours per month relative to the sample mean of 109.9 hours. Figure A2 shows the first stage and reduced form graphically.

The magnitude of the point estimate is larger than results found in prior literature where a 10 µg/m^3 increase in PM2.5 corresponds to an approximately 3-6% reduction in weekly hours worked in developing country settings. Similar studies have found a decrease in labor supply in developing countries (Aragon et al. 2017; Kim, Manley and Radoias 2017; Fan and Grainger 2023). These papers primarily study urban or national populations: Aragon, Miranda and Oliva (2017) study workers working in Lima city in Peru, Kim, Manley and Radoias (2017) estimate national effects for workers in Indonesia while Fan and Grainger (2023) focus on China. Compared to my setting, these papers focus on populations that are wealthier, enjoy higher living standards and may plausibly also have better health infrastructure in place. On the other hand, the larger effect in this paper is plausibly related to low-income, rural households exposed to very high ambient pollution levels. Furthermore, poorer baseline health and lack of adequate healthcare exacerbate pollution-induced health impacts (Balakrishnan and Tsaneva 2021).

Table 3: Impact of PM2.5 on Labor Supply

	(1) $PM_{2.5}$ *First Stage*	(2) ln(Hours) *Second Stage*
Thermal Inversions	86.70***	
	(9.59)	
$PM_{2.5}$		−0.0149***
		(0.0049)
Controls	Yes	Yes
Household FE	Yes	Yes
Season × Year FE	Yes	Yes
Observations	32,940	32,940
R^2	0.899	—
N clusters	179	179
First-stage F	81.7	

Notes. 2SLS estimates. First-stage F is the cluster-robust Kleibergen–Paap F. Standard errors, in parentheses, are clustered at the thermal-inversion grid level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.1 Heterogeneity

In this section, I focus on the heterogeneous impact of pollution on labor supply across various demographic, socioeconomic and occupational groups. For this, I allow the effect of pollution exposure to vary with individual and household characteristics. $PM_{2.5}$ and its interaction with the moderator are both treated as endogenous and instrumented by thermal inversions and their interaction with the moderator, giving the two first-stage equations:

$$\begin{aligned} \text{PM2.5}_{g,t-1} = \pi_0 + \pi_1 \text{Thermal Inversions}_{g,t-1} + \pi_2 \big(\text{Thermal Inversions}_{g,t-1} \times M_i\big) \\ + \pi_3 M_i + \pi_4 X_{i,t} + \pi_5 W_{g,t-1} + \rho_h + \gamma_{s,y} + \varepsilon_{i,t} \end{aligned} \tag{3}$$

$$\begin{aligned} \text{PM2.5}_{g,t-1} \times M_i = \omega_0 + \omega_1 \text{Thermal Inversions}_{g,t-1} + \omega_2 \big(\text{Thermal Inversions}_{g,t-1} \times M_i\big) \\ + \omega_3 M_i + \omega_4 X_{i,t} + \omega_5 W_{g,t-1} + \rho_h + \gamma_{s,y} + \eta_{i,t} \end{aligned} \tag{4}$$

The second stage is:

$$\log(\text{Hours}_{i,t}) = \beta_0 + \beta_1 \widehat{\text{PM2.5}}_{g,t-1} + \beta_2 \big(\widehat{\text{PM2.5}_{g,t-1}} \times M_i\big) + \beta_3 M_i + \beta_4 X_{i,t} + \beta_5 W_{g,t-1} + \tau_h + \delta_{s,y} + \vartheta_{i,t} \tag{5}$$

where M_i denotes the moderator (e.g., an indicator for male, outdoor work, an income tercile or an occupation group), and all other terms—Thermal Inversions$_{g,t-1}$, $X_{i,t}$, $W_{g,t-1}$, the household fixed effects ρ_h and τ_h, and the season-by-year fixed effects $\gamma_{s,y}$ and $\delta_{s,y}$—are as defined in the baseline specification. The coefficient of interest is β_2, which captures the differential effect of pollution on labor supply for individuals with $M_i = 1$ relative to the omitted group, while β_1 gives the effect for the base category. For categorical moderators (income tercile and occupation), M_i is replaced by a vector of indicators, with one endogenous interaction and one instrument interaction per non-base category. Standard errors are clustered at the thermal inversion-grid level g.

Table 4 reports heterogeneity estimates in the effect of pollution on labor supply, with each column interacting instrumented pollution with a single moderator. Column 2 reports heterogeneity estimates by gender. For women, the omitted category, a 10 µg/m^3 increase in PM2.5 reduces monthly hours worked by approximately 6.9% (7.6 hours per month), although the estimate is not statistically significant at conventional levels (-0.0069). The interaction with the male indicator is small and statistically insignificant (-0.0003), so the effect for men (-0.0072) is almost identical to that for women. The gender-specific estimates are each roughly half the magnitude of the pooled estimate in column (1). This divergence reflects a change in the composition of the workforce. Because the estimation sample is restricted to individuals who work, the pooled estimate captures both the change in hours among workers and any change in who works. A 10 µg/m^3 increase in PM2.5 raises the share of women among workers by 5.6 percentage points ($p < 0.01$). Since women work fewer hours than men on average, this compositional shift lowers mean hours worked even in the absence of any change in individual labor supply. Conditioning on gender removes this between-group component, so that the effect of pollution is identified from changes

in hours within gender. Table A7 shows that conditioning on gender reduces the baseline estimate from −0.0149 to −0.0070, indicating that approximately half of the baseline effect reflects the changing composition of workers and the remainder a reduction in hours worked conditional on gender. Consistent with this interpretation, Table A8 shows that a 10 µg/m^3 increase in PM2.5 raises women's labor force participation by 8.6 percentage points, while men's participation is unaffected. Monthly hours per adult, which include individuals who do not work and are therefore unaffected by changes in the composition of workers, fall by 4.6 hours, or 5.4 percent of the mean, although this estimate is not statistically significant.

Column 3 examines heterogeneity by education. For workers with no formal schooling, a 10 μg/m^3 increase in PM2.5 reduces monthly hours worked by approximately 13.6% ($p <$ 0.01). The interaction terms for workers with primary education (1–5 years of schooling; 0.0000, s.e. 0.0015) and with secondary education or above (6 or more years; −0.0012, s.e. 0.0013) are small and statistically insignificant. Education is commonly used as a proxy for access to information about air quality and for the capacity to engage in avoidance behavior (Fan and Grainger 2023). If the workers reduced their working hours due to informed avoidance, the response would be expected to vary systematically with education. Since this is not the case, the fall in labor supply is unlikely to arise from deliberate avoidance by better-informed workers. Instead, it points towards a more direct channel, namely the effect of pollution on workers' own health, which I examine in detail in Section 4.2.

Column 4 reports heterogeneity by income. For low-income households, the effect is negative and statistically significant (−0.0134, p $<$ 0.01). However, the interactions for higher income households are not statistically significant. This provides evidence of there being no statistically significant income gradient in the labor supply response. Column 5 reports heterogeneity by work location. For workers involved in outdoor work the implied effect is −0.0122, about 25% larger than for indoor workers. The interaction for outdoor workers is negative and statistically significant (−0.0024, p $<$ 0.05), providing evidence of their reduced supply due to having greater exposure to ambient pollution. Column 6

reports heterogeneity by occupation. I find that workers involved in farming, the base category, reduce their labor supply the most (-0.0133, $p < 0.01$). The interactions for wage labor (0.0025, $p < 0.05$) and business/self-employment (0.0028, $p < 0.05$) are positive and significant, indicating smaller effects for these groups, while salaried and other occupations do not differ significantly. Taken together with estimates from column 4, I find that the impact is somewhat larger among agricultural and outdoor workers, consistent with greater exposure to ambient pollution. Figure A3 plots out the heterogeneity estimates.

Table 4: Impact of PM2.5 on Labor Supply: Heterogeneity Estimates

	(1) Baseline	(2) Gender	(3) Education	(4) Income	(5) Outdoor	(6) Occupation
$PM_{2.5}$	-0.0149^{***}	-0.0069	-0.0136^{***}	-0.0134^{***}	-0.0098^{**}	-0.0133^{***}
	(0.0049)	(0.0043)	(0.0049)	(0.0047)	(0.0044)	(0.0043)
$PM_{2.5}\times$ Male		-0.0003				
		(0.0009)				
$PM_{2.5}\times$ Primary educ.			0.0000			
			(0.0015)			
$PM_{2.5}\times$ Secondary educ.+			-0.0012			
			(0.0013)			
$PM_{2.5}\times$ Middle income				0.0013		
				(0.0016)		
$PM_{2.5}\times$ High income				0.0003		
				(0.0015)		
$PM_{2.5}\times$ Outdoor					-0.0024^{**}	
					(0.0011)	
$PM_{2.5}\times$ Wage labor						0.0025^{**}
						(0.0012)
$PM_{2.5}\times$ Salaried						0.0020
						(0.0017)
$PM_{2.5}\times$ Business						0.0028^{**}
						(0.0011)
$PM_{2.5}\times$ Other occupation						-0.0021
						(0.0032)
First-stage F	81.7	41.0	27.7	27.1	40.8	16.5
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Season × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	32,940	32,940	32,940	32,940	32,940	32,933

Notes. Dependent variable: log monthly hours. Each column interacts $PM_{2.5}$ with one moderator; both $PM_{2.5}$ terms are instrumented by inversion frequency and its interaction with the moderator, and moderator main effects are included. The $PM_{2.5}$ row is the effect for the omitted group: whole sample (1), female (2), no schooling (3), low income (4), indoor (5) and farming (6). Primary educ.: 1–5 years; secondary educ.+: 6 or more years. All columns include baseline controls, household and season-by-year fixed effects. First-stage F is the Kleibergen–Paap F for the system. Standard errors clustered at the thermal-inversion grid level in parentheses. Full coefficients in Table A4. $^{***}\,p < 0.01$, $^{**}\,p < 0.05$, $^{*}\,p < 0.1$.

4.2 Mechanisms

I next examine why pollution reduces labor supply. The literature identifies two principal channels. First, exposure to ambient air pollution may impair workers' own health, reducing their physical capacity to work or increasing the number of days on which they are ill (Pope 2000; Aguilar-Gomez et al. 2022). Second, pollution may increase the morbidity of children and elderly household members, requiring working adults to reduce their hours in order to care for them (Aragón, Miranda and Oliva 2017; Kim, Manley and Radoias 2017). I test each channel using the survey's four-week illness module, retaining the baseline instrumental variable design:

$$Y_{iht} = \beta_1 \widehat{\text{PM2.5}}_{g,t-1} + X'_{iht}\gamma + W'_{g,t-1}\phi + \alpha_h + \delta_{sy} + \varepsilon_{iht} \tag{6}$$

where Y_{iht} is a measure of the morbidity of worker i in household h, or of the morbidity of dependents in the worker's household, in month t. $\text{PM2.5}_{g,t-1}$ is PM2.5 in grid cell g in the month before the interview, instrumented by thermal-inversion frequency $Z_{g,t-1}$ as in Equation 1. X_{iht} and $W_{g,t-1}$ are the individual controls and lagged weather controls, α_h are household fixed effects and δ_{sy} are season-by-year fixed effects. Controls, fixed effects and clustering are identical to the baseline specification. The coefficient of interest, β_1, measures the causal effect of pollution on each outcome.

To examine whether the health effects differ between men and women, I add an interaction between PM2.5 and an indicator for male workers to Equation (6):

$$Y_{iht} = \beta_1 \widehat{\text{PM2.5}}_{g,t-1} + \beta_2 \big(\text{PM2.5}\widehat{_{g,t-1} \times \text{Male}_i}\big) + \lambda\,\text{Male}_i + X'_{iht}\gamma + W'_{g,t-1}\phi + \alpha_h + \delta_{sy} + \varepsilon_{iht} \tag{7}$$

where $\text{PM2.5}_{g,t-1}$ and $\text{PM2.5}_{g,t-1} \times \text{Male}_i$ are instrumented by $Z_{g,t-1}$ and $Z_{g,t-1} \times \text{Male}_i$. The controls, weather variables and fixed effects are common to men and women.

4.2.1 Own Health

The most direct channel linking air pollution to labor supply is the worker's own health. Exposure to fine particulate matter impairs respiratory and cardiovascular function, which may increase the number of days on which a worker is ill or reduce the worker's physical capacity during the working day. This channel is likely to be particularly important in rural Bangladesh, where baseline health is poor, work is physically demanding and access to health care is limited.

Table 5 reports the results. Panel A shows that pollution worsens health and increases the incidence of illness. A 10 μg/m^3 increase in $PM_{2.5}$ raises the probability of reporting a persistent cough by 5 percentage points and the probability of any respiratory symptom by 5.5 percentage points (columns 1 and 2). It also increases the share of days on which the worker is ill by 8.4 percentage points (column 3), equivalent to approximately 2.3 additional days of illness in a four-week period, and the probability of reporting any illness by 12.6 percentage points (column 4). Column 5 reports a falsification test. Diarrhea is primarily waterborne and should not respond to air pollution. I find that the estimate is small and not statistically significant. This provides evidence that the results do not reflect a general tendency to report illness when pollution is high.

Panel B tests whether these effects differ by gender. For women, the omitted category, a 10 μg/m^3 increase in $PM_{2.5}$ raises the probability of any illness by 12.3 percentage points and the share of days ill by 8.2 percentage points, both significant at the 1 percent level. It also raises the probability of a persistent cough by 5.3 percentage points and of any respiratory symptom by 5.8 percentage points. The $PM_{2.5} \times$ Male interaction is small, ranging from -0.1 to -0.4 percentage points, and statistically insignificant for every outcome. Pollution therefore affects the health of men and women alike.

Panels C and D repeat this analysis among the workers most exposed to ambient air. For women, a 10 μg/m^3 increase in $PM_{2.5}$ raises the probability of any illness by 12.0 percentage points among outdoor workers (Panel C) and by 9.4 percentage points among farming workers

(Panel D). The $PM_{2.5}$ $\times$ Male interaction for any illness is small and insignificant in both groups (-0.3 and 0.1 percentage points). Among outdoor workers, the interaction is negative for cough, respiratory symptoms and days ill (-0.7, -0.7 and -0.8 percentage points), indicating slightly smaller effects for men, but these differences are significant only at the 10% level. Among farming workers, none of the interactions is statistically significant. Pollution therefore imposes a health burden on both male and female workers, with no evidence that it falls disproportionately on either.

Table 5: Pollution and Workers' Own Health

	(1) Persistent cough (=1)	(2) Any respiratory symptom (=1)	(3) % of days ill (0–100)	(4) Any illness (=1)	(5) Diarrhea (=1)
Panel A. All workers					
$PM_{2.5}$	0.0050**	0.0055**	0.84***	0.0126***	0.0008
	(0.0021)	(0.0022)	(0.21)	(0.0030)	(0.0008)
Mean of dep. var.	0.116	0.121	24.3	0.415	0.019
First-stage F	75.0	75.0	75.0	75.0	75.0
Observations	32,419	32,419	32,419	32,419	32,419
Panel B. All workers					
$PM_{2.5}$	0.0053**	0.0058***	0.82***	0.0123***	0.0008
	(0.0021)	(0.0022)	(0.21)	(0.0030)	(0.0008)
$PM_{2.5} \times$ Male	−0.0004	−0.0004	−0.04	−0.0001	0.0000
	(0.0003)	(0.0004)	(0.04)	(0.0005)	(0.0002)
Mean of dep. var.	0.116	0.121	24.3	0.415	0.019
First-stage F	37.6	37.6	37.6	37.6	37.6
Observations	32,419	32,419	32,419	32,419	32,419
Panel C. Outdoor workers					
$PM_{2.5}$	0.0050**	0.0057**	0.83***	0.0120***	0.0005
	(0.0023)	(0.0024)	(0.24)	(0.0032)	(0.0010)
$PM_{2.5} \times$ Male	−0.0007*	−0.0007*	−0.08*	−0.0003	0.0000
	(0.0004)	(0.0004)	(0.05)	(0.0006)	(0.0002)
Mean of dep. var.	0.117	0.122	25.2	0.427	0.019
First-stage F	31.1	31.1	31.1	31.1	31.1
Observations	25,316	25,316	25,316	25,316	25,316
Panel D. Farming workers					
$PM_{2.5}$	0.0041*	0.0051**	0.53**	0.0094***	0.0005
	(0.0023)	(0.0024)	(0.23)	(0.0032)	(0.0010)
$PM_{2.5} \times$ Male	−0.0005	−0.0004	−0.08	0.0001	−0.0001
	(0.0005)	(0.0006)	(0.06)	(0.0008)	(0.0002)
Mean of dep. var.	0.113	0.119	26.6	0.437	0.019
First-stage F	39.1	39.1	39.1	39.1	39.1
Observations	18,827	18,827	18,827	18,827	18,827

Notes. Sample: workers who answered the four-week illness module. Column (5) is a falsification outcome, since diarrhea is mainly waterborne. Panel A estimates Equation (6). Panels B–D each come from one regression adding $PM_{2.5} \times$ male and a male indicator to Equation (6), with both $PM_{2.5}$ terms instrumented by inversion frequency and its interaction with male. In Panels B–D, the $PM_{2.5}$ coefficient is the effect for women (the omitted category), and $PM_{2.5} \times$ Male is the difference between men and women; the effect for men is the sum of the two coefficients. Panel C uses outdoor workers (Table 2) and Panel D own-farm cultivators. All regressions include the baseline controls and household and season-by-year fixed effects. Coefficients are per 1 $\mu g/m^3$. Standard errors, in parentheses, are clustered at the thermal-inversion grid level. First-stage F is the cluster-robust Kleibergen–Paap F. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6 Panel B shows that the reduction in hours per day is not robust to conditioning on gender. Once a male indicator and its interaction with $PM_{2.5}$ are included, the effect on hours per day for women, the omitted category, is small and statistically insignificant (−3.9 percent), and the $PM_{2.5} \times$ Male interaction is also small and insignificant (0.6 percent). Part of the decline in Panel A therefore reflects a change in the composition of workers rather than

shorter working days for a given worker: women work fewer hours per day than men, and pollution raises the share of women among workers. By contrast, there is some evidence that men reduce the number of days they work. For women, a 10 μg/m^3 increase in $PM_{2.5}$ lowers days worked by 3.0 percent, an effect that is not statistically significant. The $PM_{2.5} \times$ Male interaction is negative and significant (-0.9 percent, $p < 0.05$), so the implied reduction for men is 3.9 percent ($p = 0.055$). Similarly, the interaction for the share of days on which workers were unable to perform their main activity is positive and significant (0.2 percentage points, $p = 0.03$). The implied effect for men (0.86 percentage points) is not statistically significant on its own. These effects are modest, and the evidence on men's days worked is significant only at the 10% level. Taken together, the results suggest that the health burden translates into lost workdays for men, while women, who are affected by illness to the same degree, continue to work.

Table 6: Pollution and the Margins of Labor Supply

	(1) Log hours per day	(2) Log days worked	(3) % of days unable to work
Panel A. All workers			
$PM_{2.5}$	-0.0125^{**}	-0.0024	0.07
	(0.0049)	(0.0020)	(0.06)
Mean of dep. var.	1.000	1.754	3.2
First-stage F	81.7	81.7	79.7
Observations	32,940	32,940	32,162
Panel B. All workers			
$PM_{2.5}$	-0.0039	-0.0030	0.06
	(0.0041)	(0.0019)	(0.06)
$PM_{2.5} \times$ Male	0.0006	-0.0009^{**}	0.02^{**}
	(0.0009)	(0.0004)	(0.01)
Mean of dep. var.	1.000	1.754	3.2
First-stage F	41.0	41.0	40.0
Observations	32,940	32,940	32,162

Notes. % of days unable to work is days in the past four weeks unable to perform the main activity (top-coded at 28), divided by 28, times 100. Panel B adds $PM_{2.5} \times$ male and a male indicator, with both $PM_{2.5}$ terms instrumented by inversion frequency and its interaction with male. In Panel B, the $PM_{2.5}$ coefficient is the effect for women (the omitted category), and $PM_{2.5} \times$ Male is the difference between men and women; the effect for men is the sum of the two coefficients. All regressions include the baseline controls and household and season-by-year fixed effects. Standard errors, in parentheses, are clustered at the thermal-inversion grid level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

4.2.2 Caregiving

An alternative explanation is that pollution reduces labor supply by increasing the demand for care within the household. Studies from Peru, Indonesia and South Korea find that workers, particularly women, reduce their hours to care for children and elderly relatives made ill by pollution (Aragón, Miranda and Oliva 2017; Kim, Manley and Radoias 2017; Han et al. 2023). If this channel operated in rural Bangladesh, pollution should increase the morbidity of dependents, and the reduction in hours should be larger in households that contain them. I test both predictions in Table 7.

Table 7 panel A reports the results for all workers. Columns (1)–(4) estimate the effect of pollution on the morbidity of children aged five and under and adults aged 65 and over living in the worker's household. The estimates are small and statistically insignificant for every measure, including respiratory illness among young children. Column (5) allows the effect of pollution on hours worked to differ between households with and without a susceptible member, which account for 47 percent of the sample. The interaction term is small (-0.0003) and statistically insignificant, indicating that the reduction in hours is no larger in households with young children or elderly members. In column 6, I interact pollution with gender and the presence of susceptible members in the household to see if women reduce their labor supply to care for dependents. I find that the estimate is small and not statistically significant (-0.0025). This provides evidence of women in households with susceptible members not reducing their hours worked more than other workers. The PM2.5 coefficient in column (6), -0.0076, is the effect for men in households without such members; it is smaller than in column (5) because the regression now controls for gender, which accounts for the change in the composition of workers discussed above.

Taken together, these results suggest that caregiving is not the channel through which pollution reduces labor supply in this setting. Pollution does not increase illness among children or elderly members of workers' households, the reduction in hours is no larger in households with dependents, and women in such households do not reduce their hours more than other workers. I therefore find no evidence that caregiving drives the labor supply response in rural Bangladesh. The evidence instead points to the direct effect of pollution on workers' own health, which affects men and women alike and translates into lost workdays for men. This contrasts with evidence from urban and middle-income settings, where caregiving plays a central role.

Table 7: Testing the Caregiving Channel

	Morbidity of dependents				*Hours worked*	
	(1) Any dependent ill	(2) Child under 5 ill	(3) Child under 5 with cough	(4) Elderly member ill	(5) Log monthly hours	(6) Log monthly hours
$PM_{2.5}$	0.0036	0.0037	0.0041	0.0028	−0.0147***	−0.0076*
	(0.0034)	(0.0032)	(0.0027)	(0.0022)	(0.0051)	(0.0045)
$PM_{2.5}$ × susceptible household					−0.0003	0.0015
					(0.0012)	(0.0012)
$PM_{2.5}$ × female						0.0014
						(0.0013)
$PM_{2.5}$ × susceptible household × female						−0.0025
						(0.0017)
Mean of dep. var.	0.319	0.240	0.137	0.109	4.221	4.221
First-stage F	81.7	81.7	81.7	81.7	39.9	20.1
Observations	32,940	32,940	32,940	32,940	32,940	32,940

Notes. Columns (1)–(4): indicators for illness in the four-week module of household members other than the respondent, namely children aged five and under and adults aged 65 and over, assigned to each working-age respondent. Column (5) interacts PM2.5 with an indicator for a household containing such members (47.0 percent of the sample), instrumented by the matching interaction of inversion frequency. Its PM2.5 coefficient is the effect in households without such members. Column (6) adds PM2.5 × female and the triple interaction, with all PM2.5 terms instrumented likewise. Its PM2.5 coefficient is the effect for men in households without such members, and the triple interaction is the additional response of women in households with such members. Main effects of all moderators are included. All columns include the baseline controls and household and season-by-year fixed effects. Standard errors, in parentheses, are clustered at the thermal-inversion grid level. First-stage F is the cluster-robust Kleibergen–Paap F. $^{***}\,p < 0.01$, $^{**}\,p < 0.05$, $^{*}\,p < 0.1$.

4.3 Robustness Checks

I conduct a series of robustness checks to examine whether the baseline estimate is sensitive to the main choices made in the empirical specification.

4.3.1 Thermal Inversion Strength

The instrument of thermal inversions that I have used measures the frequency of thermal inversions, that is, the share of hours in the month during which the temperature at 925 hPa exceeds the temperature at 1000hPa. An alternative approach to constructing the instrument would involve measuring how strong the inversions are as larger temperature differences across the layers would trap pollutants more effectively (Yamada and Narita

2025; Bhattacharjee and Saha 2025). Therefore, I re-estimate the equation using thermal inversion strength as an instrument. This is defined as the average positive temperature difference between 925 hPa and 1000 hPa across all hours of the month. Table 8 reports the result. A 10 $\mu g/m^3$ increase in PM2.5 is associated with a 17.9% reduction in monthly hours worked, a loss of roughly 19.7 hours per month relative to the sample mean of 109.9 hours.

Table 8: Robustness to Measuring Inversion Strength

	(1) Baseline: inversion frequency	(2) Inversion strength
Panel A. Second stage: ln(*monthly hours*)		
$PM_{2.5}$	-0.0149^{***}	-0.0179^{**}
	(0.0049)	(0.0088)
Panel B. First stage: $PM_{2.5}$		
Inversion instrument	86.70^{***}	22.50^{***}
	(9.59)	(4.11)
First-stage F	81.7	29.9
Weather controls	Continuous	Continuous
Fixed effects	Household + Season × Year	Household + Season × Year
SE clustering	TI grid	TI grid
Observations	32,940	32,940
Clusters	179	179

Notes. Dependent variable: log monthly hours worked. Column (1) is the baseline, instrumenting PM2.5 with inversion frequency (share of hours with $T_{925} > T_{1000}$). Column (2) uses average inversion strength, the monthly mean of $\max(T_{925} - T_{1000}, 0)$ in °C. All columns include the baseline controls and household and season-by-year fixed effects. First-stage F is the cluster-robust Kleibergen–Paap F. Standard errors, in parentheses, are clustered at the thermal-inversion grid level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

4.3.2 Weather Persistence

A potential threat to the exclusion restriction arises from the persistence of weather conditions. Thermal inversions form under cold and dry conditions, and these conditions may persist across several months. Inversions in the month in which pollution is measured may

be correlated with weather in the month in which hours are worked. Because weather in that month can affect labor supply directly, through rainfall, heat stress or the timing of agricultural activities, the baseline specification, which conditions only on weather in the pollution month, may attribute to pollution part of the effect of subsequent weather. To address this concern, I augment the baseline specification and control for weather in the month in which hours are worked. Table 9 reports the results. A 10 µg/m* increase in PM2.5 reduces monthly hours worked by 21.2%, a loss of roughly 23.3 hours per month relative to the sample mean of 109.9 hours. This suggests that the baseline result is not driven by the persistence of weather conditions between the month of exposure and the month in which hours are worked and, if anything, understates the effect of pollution on labor supply.

Table 9: Robustness to Flexible Weather Controls

	(1) Baseline	(2) Weather in $t-1$ and t
$PM_{2.5}$	-0.0149^{***}	-0.0212^{**}
	(0.0049)	(0.0085)
First-stage F	81.7	28.9
Weather controls, $t-1$	Yes	Yes
Weather controls, t	No	Yes
Individual controls	Yes	Yes
Fixed effects	Household + Season × Year	Household + Season × Year
SE clustering	TI grid	TI grid
Observations	32,940	32,940
Clusters	179	179

Notes. Dependent variable: log monthly hours worked. t is the month in which hours are worked and $t-1$ the month in which PM2.5 is measured. Weather controls (precipitation, temperature, wind speed, surface pressure, relative humidity; ERA5) enter linearly and separately for each month indicated. Column (1) is the baseline. Column (2) adds weather in month t. All columns include the baseline individual controls and household and season-by-year fixed effects. First-stage F is the cluster-robust Kleibergen–Paap F. Standard errors, in parentheses, are clustered at the thermal-inversion grid level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

4.3.3 Within Season Trends

In the baseline specification, I include season by year fixed effects. This shows that the effect of pollution is identified from differences in inversion frequency among households interviewed in the same season of the same year. Within a season, however, interviews may have taken place across different months, and both inversions and labor supply may evolve systematically over these months. In the dry winter months, with colder nights and more frequent inversions, the demand for agricultural labor also changes with the stage of the crop cycle. If these patterns coincide, then the baseline estimate would partly be reflecting the timing of the interviews within the season instead of the effect of pollution.

To account for this, I include a linear trend in the month of interview in my specification as below:

$$\ln(\text{Hours})_{iht} = \beta_1 \widehat{\text{PM2.5}}_{g,t-1} + \theta\, m_t + X'_{iht}\gamma + W'_{g,t-1}\phi + \alpha_h + \delta_{sy} + \varepsilon_{iht} \tag{8}$$

where m_t is the number of months elapsed between January 2011 and the month of interview, and δ_{sy} are season-by-year fixed effects. Because δ_{sy} absorbs the level of each season in each year, the trend captures only the linear change in hours worked across the months within a season, with a common slope across seasons. β_1 is therefore identified from variation in inversion frequency beyond what would be expected at that point in the season.

Table 10 reports the results. A 10 µg/m^3 increase in PM2.5 reduces monthly hours worked by 16.0 percent, or approximately 17.6 hours per month at the sample mean. The estimate is nearly identical to the baseline of 14.9 percent, indicating that the results are not driven by gradual within-season changes in inversions and labor supply.

Table 10: Robustness to Within-Season Trends

	(1) Baseline	(2) Adding monthly trend
Panel A. Second stage: ln(*monthly hours*)		
$PM_{2.5}$	-0.0149^{***}	-0.0160^{***}
	(0.0049)	(0.0053)
Panel B. First stage: $PM_{2.5}$		
Thermal inversions	86.70^{***}	81.10^{***}
	(9.59)	(9.34)
First-stage F	81.7	75.4
Linear trend in interview month	No	Yes
Weather controls	Yes	Yes
Individual controls	Yes	Yes
Fixed effects	Household + Season × Year	Household + Season × Year
SE clustering	TI grid	TI grid
Observations	32,940	32,940
Clusters	179	179

Notes. Dependent variable: log monthly hours worked. Column (1) is the baseline. Column (2) adds a linear trend in months since January 2011 to both stages; with season-by-year fixed effects, it captures steady changes across the months within each season. All columns include the baseline controls and household and season-by-year fixed effects. First-stage F is the cluster-robust Kleibergen–Paap F. Standard errors, in parentheses, are clustered at the thermal-inversion grid level. $^{***}\,p < 0.01$, $^{**}\,p < 0.05$, $^{*}\,p < 0.1$.

4.3.4 Attrition

The analysis follows the same households across 3 waves. Between the first and second wave, 11% of workers drop out of the sample; between the second and third, 33.9% of workers do. A worker can leave the sample either because the household was not being re-interviewed or because they are no longer a member of the household due to migration, marriage or death[2]. This raises the concern that the estimation sample is selected on the outcome. If pollution worsens health and the most affected individuals re-locate and leave the panel,

[2]Much of the attrition between 2015 and 2018–19 reflects survey design rather than respondent behavior: one sample stratum of 865 households, concentrated in Barisal and Khulna divisions, was not revisited in the third round. Excluding this stratum, 9.6% of workers observed in 2015 belong to households that were not re-interviewed in 2018-19

then the remaining workers would not be representative of those exposed, leading to a biased estimate of the impact of pollution (Verbeek and Nijman 1992). Attrition does not bias the estimates if it is unrelated to the variation that identifies the effect, or if those who leave the sample do not differ in their labor supply in ways that the fixed effects do not absorb. I examine both conditions in Table 11.

First, I examine whether the identifying variation predicts attrition. For this, I estimate the specification below following Kim, Manley and Radoias (2017) and Hanna and Oliva (2015):

$$A_{it} = \theta Z_{it} + X'_{it}\gamma + W'_{it}\phi + \alpha_h + \delta_{sy} + \varepsilon_{it} \tag{9}$$

where $A_{it} = 1$ if worker i, observed in round t, is no longer a member of a surveyed household in round $t+1$, and Z_{it} is the frequency of thermal inversions. X_{it} and W_{it} are the individual and weather controls, α_h are household fixed effects and λ_s are season fixed effects. Table 11, column (2), reports the results. A one-standard-deviation increase in thermal inversions changes the probability of leaving the sample by less than 0.1 percentage points, relative to a mean of 22.5 percent.

Next, I examine whether individuals who leave differ in their labor supply. For this, I include an indicator D_{ht} equal to one if household h is not re-interviewed in the next round following Verbeek and Nijman (1992) as below:

$$\ln H_{it} = \beta \widehat{\mathrm{PM}}_{it} + \kappa D_{ht} + X'_{it}\gamma + W'_{it}\phi + \alpha_h + \delta_{sy} + \varepsilon_{it} \tag{10}$$

where $D_{ht} = 1$ if household h leaves the sample after round t, and all other terms are as in Equation (9). Table 11, column (3), reports the results. The estimate of κ is small and statistically insignificant (0.064, s.e. 0.048), and the estimated effect of PM2.5 is essentially unchanged relative to the baseline (-0.0152 compared with -0.0149).[3] Together with the

[3]Following Aragón, Miranda and Oliva (2017), the indicator equals one if the household is not re-interviewed in the following round and zero otherwise, so that all three rounds are retained in the estimation.

results in column (2), this indicates that attrition is unrelated to the instrument and to labor supply, and does not account for the estimated effect of pollution on hours worked.

Table 11: Robustness to Attrition

	(1) Baseline	(2) Attrition as outcome	(3) Attrition as regressor
Dependent variable	ln(hours)	Leaves sample next round	ln(hours)
$PM_{2.5}$	-0.0149^{***}		-0.0152^{***}
	(0.0049)		(0.0050)
Thermal inversions		-0.013	
		(0.227)	
Household leaves panel next round			0.064
			(0.048)
First-stage F	81.7		77.9
Mean of dependent variable		0.225	
Estimator	2SLS	OLS	2SLS
Individual and weather controls	Yes	Yes	Yes
Fixed effects	Household + Season × Year	Household + Season × Year	Household + Season × Year
SE clustering	TI grid	TI grid	TI grid
Observations	32,940	22,798	32,940
Clusters	179	179	179

Notes. Column (1) is the baseline. Column (2) follows Hanna and Oliva (2015) and Kim, Manley and Radoias (2017): an indicator for a worker observed in 2011–12 or 2015 leaving the surveyed household by the next round is regressed on thermal inversions by OLS, adding age squared and sex as controls. Column (3) implements the Verbeek and Nijman (1992) test, following Aragón, Miranda and Oliva (2017), by adding an indicator for the household not being re-interviewed next round; it is set to zero in 2018–19, and estimating on 2011–12 and 2015 only gives -0.023 (s.e. 0.035). All columns include the baseline controls and household and season-by-year fixed effects. First-stage F is the cluster-robust Kleibergen–Paap F. Standard errors, in parentheses, are clustered at the thermal-inversion grid level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

4.3.5 Migration

The last section established that attrition does not bias the estimates. This section helps to address migration as it can affect the labor supply of individuals who have remained in

Excluding the final round, in which the indicator is undefined (Wooldridge, 2010), and estimating the test by OLS on the 2011–12 and 2015 rounds yields a similar, statistically insignificant coefficient (-0.023, s.e. 0.035).

the estimation sample. When an individual migrates, it may impact the labor supply of remaining household members who continue to be observed, so any effect of the migrant on the latter is not captured by attrition. These effects can operate in two ways. First, it could be that the remaining workers now work more hours to replace the income of the departed member. On the other hand, the departed member may send back remittances which help supplement household income and reduce the need for the remaining members to work. These effects bias the estimates only if migration of this kind is correlated with the instrument. When a member leaves for reasons unrelated to pollution such as employment, education or marriage, the resulting change in the labor supply of those left behind is not systematically related to thermal inversion. They are therefore absorbed by the error term and do not bias the instrumental-variable estimate. Any persistent differences between households that send migrants and those that do not are absorbed by the household fixed effects.

Bias arises only if migration is correlated with pollution exposure, either because pollution itself induces household members to migrate, or because migration and thermal inversions follow similar seasonal patterns. In either case, part of the estimated effect of PM2.5 on hours worked could reflect the reorganization of household labor following a member's departure, rather than the direct effect of pollution on workers.

To test for migration, I re-run the baseline specification by excluding, in all survey rounds, every household in which a member migrated between the 2011–12 and 2018–19 survey rounds. Migrants are identified from BIHS Module V1, which records every household member who has been away for more than six months since the previous survey round, together with the timing and purpose of the move. Over the survey period, 1,547 households in the estimation sample, 26% of the total, report at least one migrant; excluding them removes the 4,560 workers who remained in these households. Because the data does not contain information on whether the migration was related to pollution, the exclusion applies to all households that sent a migrant, regardless of the reason for migration. The effect of pollution is then identified only from households that never send a migrant.[1]

Column 2 of Table 12 reports the results.[4] The instrument remains strong, with a first-stage F-statistic of 34.1. The estimated effect of PM2.5 is virtually unchanged relative to the baseline estimate of -0.0149, at -0.0147 (s.e. 0.0076), although it is less precisely estimated given the smaller sample. The fall in labor supply therefore occurs among workers in households that do not send migrants. This indicates that migration does not account for the estimated effect of pollution on labor supply.

Table 12: Robustness to Migration

	(1) Baseline	(2) Excluding households with a migrant during the survey period
$PM_{2.5}$	-0.0149^{***}	-0.0147^{*}
	(0.0049)	(0.0076)
First-stage F	81.7	34.1
Weather controls	Yes	Yes
Individual controls	Yes	Yes
Fixed effects	Household + Season × Year	Household + Season × Year
SE clustering	TI grid	TI grid
Observations	32,940	23,998
Clusters	179	179

Notes. Dependent variable: log monthly hours worked. Column (1) is the baseline. Column (2) drops, in all rounds, households with any member away for more than six months between the 2011–12 and 2018–19 rounds (BIHS Module V1; 1,547 households). All columns include the baseline controls and household and season-by-year fixed effects. First-stage F is the cluster-robust Kleibergen–Paap F. Standard errors, in parentheses, are clustered at the thermal-inversion grid level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

4.3.6 Placebo Tests

The identification strategy rests on the assumption that thermal inversions affect labor supply only through their effect on pollution. This assumption would be violated if thermal

[4]Households that send migrants are retained in the baseline specification. Because migration that is unrelated to the instrument does not bias the estimates, excluding these households is not required for identification, and doing so would remove a quarter of the sample and reduce its representativeness of rural Bangladesh. The exclusion is therefore reported as a robustness check rather than imposed in the baseline.

inversions were correlated with labor supply for reasons unrelated to pollution for example because they coincide with particular periods or locations that also shape hours worked. I examine this possibility using two placebo tests. The first test uses future inversions while the second randomly reassigns inversions across locations. Table 13 presents the results.

In the first placebo test, I exploit the timing of the labor supply measure and use future instead of past thermal inversions. Since these are observed after the period in which working hours are reported, they cannot impact labor supply. I find that the estimate is negative and not statistically significant (-0.0081 compared with -0.0149 in the baseline). This provides evidence of future inversions not predicting labor supply, consistent with the estimated effect operating through pollution exposure.

In the second placebo test, I examine whether the estimated impact depends on the actual location of inversions. For this, I randomly assign thermal inversions across locations. I do this by reassigning inversions occurring in the same month across households but elsewhere in the country. If the baseline estimate determines the impact of local inversions on local pollution, randomly assigned inversions should not produce a systematic effect of pollution on labor supply. I find that the estimated effect is smaller in magnitude and not statistically significant (-0.0071).

Table 13: Placebo Tests

	(1) Baseline	(2) Placebo: future inversions	(3) Placebo: randomly assigned inversions
$PM_{2.5}$	-0.0149^{***}	-0.0081	-0.0071
	(0.0049)	(0.0066)	(0.0055)
First-stage F	81.7	84.4	52.2
Weather controls	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes
Fixed effects	Household + Season × Year	Household + Season × Year	Household + Season × Year
SE clustering	TI grid	TI grid	TI grid
Observations	32,940	32,940	32,940
Clusters	179	179	179

Notes. Dependent variable: log monthly hours worked. Column (1) is the baseline. Column (2) instruments PM2.5 in the interview month, after hours were worked, with interview-month inversions, controlling for the baseline instrument and interview-month weather. Column (3) instruments PM2.5 with inversions randomly reassigned across the 179 grid cells within each calendar month. All columns include the baseline controls and household and season-by-year fixed effects. First-stage F is the cluster-robust Kleibergen–Paap F. Standard errors, in parentheses, are clustered at the thermal-inversion grid level. $^{***}\,p < 0.01$, $^{**}\,p < 0.05$, $^{*}\,p < 0.1$.

5 Conclusion

This paper examines the impact of fine particulate matter on labor supply in rural Bangladesh. Using thermal inversions as an instrument for pollution exposure, I estimate a negative effect of PM2.5 on monthly hours worked, with a 10 µg/m3 increase in PM2.5 associated with a reduction in monthly working hours of approximately 14.9%. The effect is somewhat larger for outdoor and agricultural workers although it does not differ significantly by gender or household income. The mechanism analysis shows that pollution increases respiratory symptoms and days of illness among both male and female workers, and that men respond by working fewer days, but does not affect the health of dependents, and women in households with dependents do not reduce their hours more than other workers. This indicates that the reduction in labor supply reflects workers' own health rather than caregiving responsibili-

ties. These results are robust to alternative instrument definitions, flexible weather controls, within-season trends, attrition, migration and placebo tests.

To my knowledge, this paper provides the first causal evidence of the impact of pollution on rural working hours in Bangladesh, extending current literature on pollution and labor supply. While current literature primarily focuses on urban or developed settings (Aragon, Miranda and Oliva 2017; Hanna and Oliva 2015), research examining pollution-induced health impacts among rural workers is scarce (Chan, Pelli and Vienne 2023). Compared to earlier research, my estimates are larger, plausibly because my sample is composed of low-income, rural households exposed to very high ambient pollution levels and having limited means to avoid pollution exposure. Consistent with prior literature, I find that the effect is somewhat larger among outdoor and agricultural workers as they are especially sensitive to pollution (Graff Zivin and Neidell 2012; Ye, Huang, and Chen 2023). My results depart from papers finding women being more adversely impacted by pollution than men (Kim, Manley and Radoias 2017; Han et al. 2023). I find that my results have no differential effect by gender or income, either on hours or on health, and no evidence that women reduce their work to care for dependents, in contrast to evidence from urban and middle-income settings (Aragon, Miranda and Oliva 2017; Han et al. 2023).

It is also important to note that the use of satellite-based pollution estimate, as is done in this paper, is prone to result in downward bias at higher pollution levels due to which these results are likely underestimating the true impact of pollution on labor supply (Fowlie, Knittel and Wolfram 2012). Several limitations of the analysis point to avenues for future research. The adoption of stronger or alternative instruments can help sharpen inference. Furthermore, improving the flexibility of the IV framework to accommodate non-linear and heterogeneous effects of pollution on working hours remains a further direction. Findings from this paper suggest that air pollution poses high labor market costs in low-income, developing countries such as Bangladesh.

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Appendix A

Table A1: Descriptive Statistics, Estimation Sample

Variable	Obs	Mean	Std. Dev.	Min	Max
Panel A: Working hours					
Monthly hours	32,940	109.866	94.118	0.433	364.000
Log monthly hours	32,940	4.222	1.088	−0.836	5.897
Panel B: Demographics and work					
Age	32,940	36.920	12.671	15.000	64.000
Education	32,940	4.145	4.014	0.000	16.000
Household size	32,940	4.748	1.813	1.000	20.000
Married	32,940	0.810	0.393	0.000	1.000
Male	32,940	0.507	0.500	0.000	1.000
Occupation: Farming	32,933	0.603	0.489	0.000	1.000
Occupation: Wage labor	32,933	0.141	0.348	0.000	1.000
Occupation: Salaried	32,933	0.052	0.222	0.000	1.000
Occupation: Business (self-emp./trader)	32,933	0.190	0.392	0.000	1.000
Occupation: Other (prod./livestock)	32,933	0.013	0.113	0.000	1.000
Outdoor work	32,940	0.792	0.406	0.000	1.000
Income tercile: Low	32,940	0.202	0.401	0.000	1.000
Income tercile: Middle	32,940	0.361	0.480	0.000	1.000
Income tercile: High	32,940	0.438	0.496	0.000	1.000
Panel C: Pollution, thermal inversions and weather					
PM2.5 (μg/m^3)	32,940	94.191	35.243	19.800	225.300
Thermal inversions	32,940	13.868	16.937	0.000	128.000
Precipitation (mm)	32,940	54.068	108.436	0.001	796.182
Temperature (°C)	32,940	21.909	3.757	14.504	29.556
Wind speed (m/s)	32,940	1.914	0.501	0.789	5.105
Air pressure (hPa)	32,940	1,010.275	7.114	933.440	1,017.979
Relative humidity (%)	32,940	77.878	5.160	60.518	89.583

Notes: The estimation sample is the baseline household fixed-effects sample of Table 3: 32,940 individual-round observations of workers aged 15–64 in 5,877 households, after households observed in only one wave are dropped as singletons. Thermal inversions are the share of hours in the month in which the temperature at 925 hPa exceeds the temperature at 1000 hPa (ERA5). Pollution, inversions and weather are measured a month before the interview. Income terciles are of household labor income.

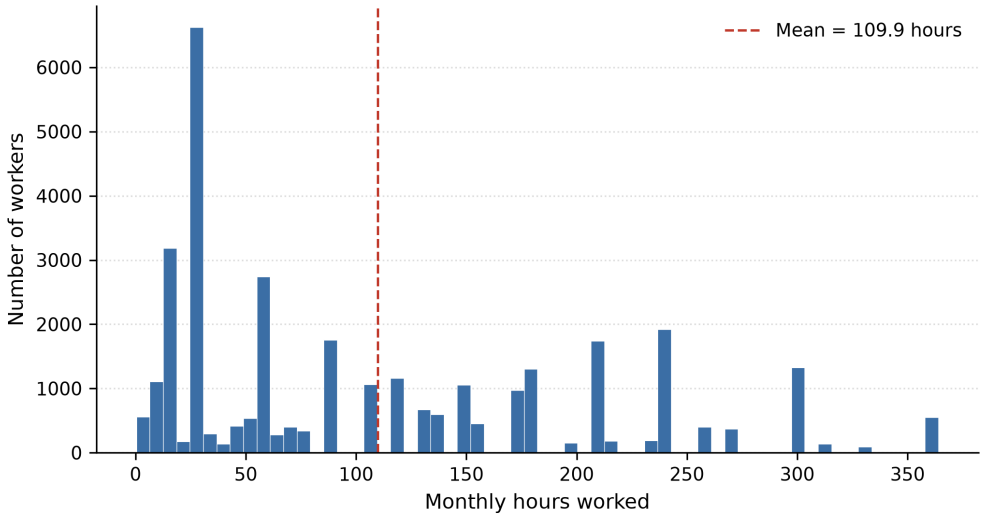


Figure A1: Distribution of Monthly Hours Worked

Note: Monthly hours worked in the primary activity (weekly hours scaled by 52/12) for the 32,940 observations in the estimation sample, trimmed at the top 1%. The dashed line marks the mean (109.9 hours). The distribution is right-skewed.

Table A2: OLS, Reduced Form, First Stage, and 2SLS Estimates

	(1) OLS ln(Hours)	(2) Reduced form ln(Hours)	(3) First stage $PM_{2.5}$	(4) 2SLS ln(Hours)
Thermal inversions		-1.296^{***}	86.70^{***}	
		(0.384)	(9.59)	
$PM_{2.5}$	0.0005			-0.0149^{***}
	(0.0004)			(0.0049)
Controls	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Season × Year FE	Yes	Yes	Yes	Yes
Observations	32,940	32,940	32,940	32,940
R^2	0.248	0.249	0.899	
N clusters	179	179	179	179
First-stage F				81.7

Notes. Column (1) is the OLS regression of log monthly hours on $PM_{2.5}$; column (2) regresses log monthly hours on thermal-inversion frequency (the reduced form); column (3) regresses $PM_{2.5}$ on the same instrument (the first stage); column (4) is the 2SLS estimate of Table 3. All four columns use the same sample. The 2SLS estimate equals the ratio of the reduced-form to the first-stage coefficient ($-1.296/86.70 = -0.0149$). Controls are age, education, household size and marital status, and weather (precipitation, temperature, wind speed, surface pressure, relative humidity) in the month in which $PM_{2.5}$ is measured. All columns include household and season-by-year fixed effects. Standard errors, in parentheses, are clustered at the thermal-inversion grid level (179 cells). First-stage F is the cluster-robust Kleibergen–Paap F on the excluded instrument. Households observed in only one wave are singletons under household fixed effects and drop out. $^{***}\,p < 0.01$, $^{**}\,p < 0.05$, $^{*}\,p < 0.1$.

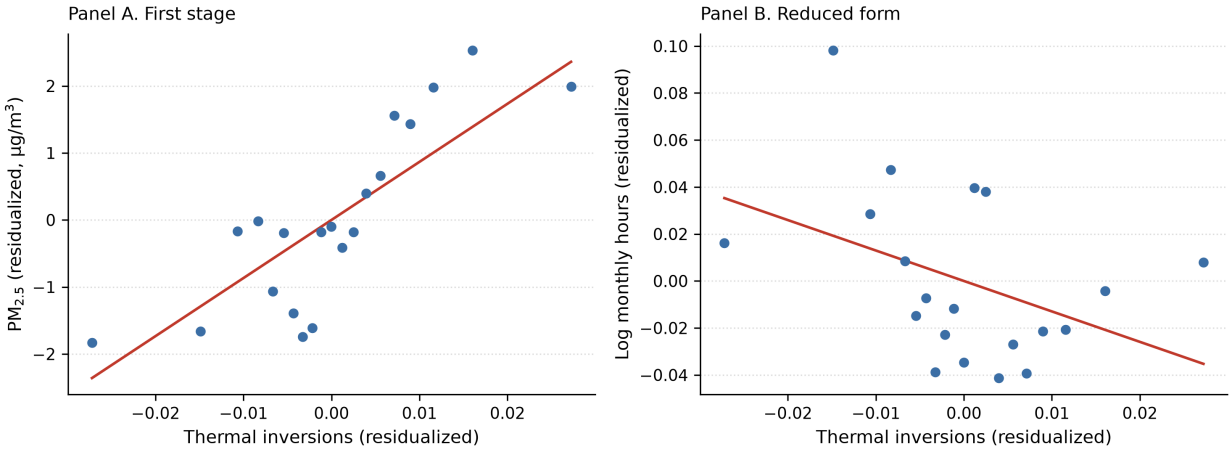


Figure A2: First Stage and Reduced Form

Note: Panel A plots PM2.5 against the thermal-inversion instrument; panel B plots log monthly hours worked against the same instrument. Both variables are residualized on household and season-by-year fixed effects and the baseline controls (age, education, household size, marital status, weather); points are means within 20 equal-sized bins of the residualized instrument and the red lines are the regression fits, estimated on the 32,940 observations of the estimation sample. Thermal inversions raise pollution (panel A; slope 86.7, Kleibergen–Paap F = 81.7) and reduce hours worked (panel B; slope -1.30). The ratio of the two slopes, -1.296/86.7 = -0.0149, equals the 2SLS estimate in Table 3.

Table A3: Impact of PM2.5 on Labor Supply (All Controls)

	(1) $PM_{2.5}$ *First stage*	(2) ln(Hours) *Second stage*
Thermal inversions	86.70***	
	(9.59)	
$PM_{2.5}$		−0.0149***
		(0.0049)
Age	0.0009	0.0189***
	(0.0060)	(0.0010)
Education	−0.0105	0.0254***
	(0.0222)	(0.0036)
Household size	−0.2447	0.0265***
	(0.1654)	(0.0069)
Married	0.3819**	−0.2271***
	(0.1910)	(0.0252)
Precipitation	−0.0242***	−0.0002
	(0.0032)	(0.0002)
Temperature	−5.2118***	−0.0736***
	(0.2334)	(0.0258)
Wind speed	−9.5775***	−0.1024*
	(1.0716)	(0.0614)
Air pressure	2.5797***	0.0359*
	(0.3802)	(0.0202)
Relative humidity	0.9149***	0.0127**
	(0.0896)	(0.0058)
Household FE	Yes	Yes
Season × Year FE	Yes	Yes
Observations	32,940	32,940
R^2	0.899	—
N clusters	179	179
First-stage F	81.7	

Notes. Full set of coefficients for Table 3. Column (1) is the first-stage regression of $PM_{2.5}$ on thermal-inversion frequency; column (2) is the 2SLS estimate of log monthly hours on instrumented $PM_{2.5}$. Weather variables are measured in the month in which $PM_{2.5}$ is measured. All columns include household and season-by-year fixed effects. Standard errors, in parentheses, are clustered at the thermal-inversion grid level (179 cells). First-stage F is the cluster-robust Kleibergen–Paap F on the excluded instrument. Households observed in only one wave are singletons under household fixed effects and drop out. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

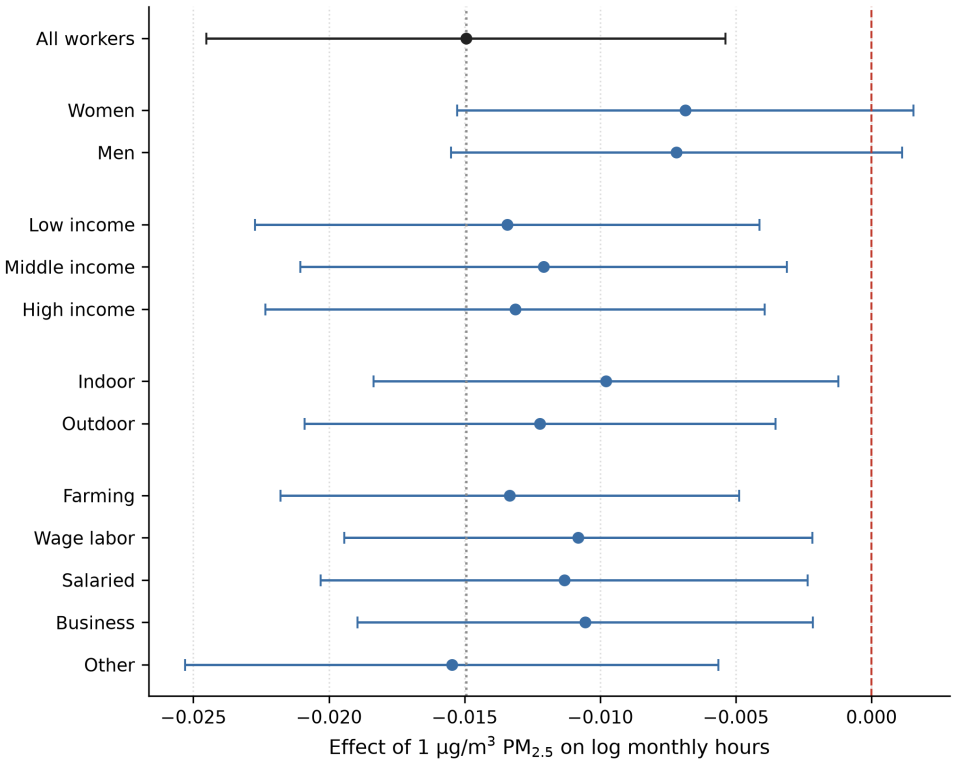


Figure A3: Heterogeneity in the Effect of PM2.5 on Labor Supply

Note: Each marker is the 2SLS estimate of the effect of a 1 µg/m^3 increase in PM2.5 on log monthly hours from Tables 8 till 13, with 95% confidence intervals. The red dashed line is zero; the grey dotted line is the baseline estimate (−0.0149). The placebo estimates (orange) use future inversions and inversions randomly reassigned across locations. Standard errors are clustered at the thermal-inversion grid level.

Table A4: Impact of PM2.5 on Labor Supply: Heterogeneity Estimates (All Controls)

	(1) Baseline	(2) Gender	(3) Education	(4) Income	(5) Outdoor	(6) Occupation
$PM_{2.5}$	−0.0149***	−0.0069	−0.0136***	−0.0134***	−0.0098**	−0.0133***
	(0.0049)	(0.0043)	(0.0049)	(0.0047)	(0.0044)	(0.0043)
$PM_{2.5}$ × Male		−0.0003				
		(0.0009)				
$PM_{2.5}$ × Primary educ.			0.0000			
			(0.0015)			
$PM_{2.5}$ × Secondary educ.+			−0.0012			
			(0.0013)			
$PM_{2.5}$ × Middle income				0.0013		
				(0.0016)		
$PM_{2.5}$ × High income				0.0003		
				(0.0015)		
$PM_{2.5}$ × Outdoor					−0.0024**	
					(0.0011)	
$PM_{2.5}$ × Wage labor						0.0025**
						(0.0012)
$PM_{2.5}$ × Salaried						0.0020
						(0.0017)
$PM_{2.5}$ × Business						0.0028**
						(0.0011)
$PM_{2.5}$ × Other occupation						−0.0021
						(0.0032)
Male		1.4481***				
		(0.0897)				
Primary educ.			−0.1948			
			(0.1426)			
Secondary educ.+			−0.4698***			
			(0.1355)			
Middle income				0.2146		
				(0.1478)		
High income				0.4644***		
				(0.1420)		
Outdoor					−0.9668***	
					(0.1013)	
Wage labor						1.1991***
						(0.1114)
Salaried						1.6179***
						(0.1612)
Business						1.3272***
						(0.1027)
Other occupation						1.1539***
						(0.3292)
Age	0.0189***	0.0028***	0.0180***	0.0189***	0.0166***	0.0144***
	(0.0010)	(0.0006)	(0.0010)	(0.0010)	(0.0009)	(0.0007)
Education (years)	0.0254***	−0.0172***	0.0832***	0.0248***	0.0010	−0.0017
	(0.0036)	(0.0023)	(0.0067)	(0.0036)	(0.0032)	(0.0024)
Household size	0.0265***	−0.0048	0.0266***	0.0033	0.0133**	−0.0009
	(0.0069)	(0.0057)	(0.0069)	(0.0067)	(0.0062)	(0.0059)
Married	−0.2271***	0.1949***	−0.2205***	−0.2231***	−0.1406***	−0.0161
	(0.0252)	(0.0197)	(0.0250)	(0.0247)	(0.0211)	(0.0173)
Precipitation	−0.0002	0.0000	−0.0001	−0.0001	−0.0001	−0.0001
	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Temperature	−0.0736***	−0.0387*	−0.0695***	−0.0627**	−0.0468**	−0.0679***
	(0.0258)	(0.0224)	(0.0256)	(0.0247)	(0.0235)	(0.0236)
Wind speed	−0.1024*	−0.0528	−0.0945	−0.0843	−0.0483	−0.1331**
	(0.0614)	(0.0527)	(0.0610)	(0.0612)	(0.0563)	(0.0553)
Air pressure	0.0359*	0.0079	0.0321	0.0312	0.0407**	0.0163
	(0.0202)	(0.0167)	(0.0197)	(0.0193)	(0.0194)	(0.0178)
Relative humidity	0.0127**	0.0016	0.0114**	0.0124**	0.0114**	0.0048
	(0.0058)	(0.0050)	(0.0058)	(0.0056)	(0.0056)	(0.0052)
First-stage F	81.7	41.0	27.7	27.1	40.8	16.5
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Season × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	32,940	32,940	32,940	32,940	32,940	32,933

Notes. Full set of coefficients for Table 4. Dependent variable: log monthly hours. Each column interacts instrumented $PM_{2.5}$ with one moderator; $PM_{2.5}$ and each interaction are instrumented by inversion frequency and inversion frequency × moderator, and the moderator main effects are included. The $PM_{2.5}$ row is the effect for the omitted group: whole sample (col. 1), female (col. 2), no schooling (col. 3), low-income tercile (col. 4), indoor (col. 5) and farming (col. 6). Primary educ. is 1–5 years of schooling; secondary educ.+ is 6 or more years. Business refers to self-employed workers and traders. Column (3) includes both years of education (a baseline control) and the education-group indicators; the indicators capture departures from a linear effect of schooling. All columns include household and season-by-year fixed effects. Standard errors, in parentheses, are clustered at the thermal-inversion grid level (179 cells). First-stage F is the cluster-robust Kleibergen–Paap rk Wald F on the excluded instruments; with several endogenous regressors, it is the F for the system. Singleton observations are dropped. Households observed in only one wave remain in the sample but contribute no identifying variation, since pollution and the instrument do not vary within them.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5: Robustness of the Effect of PM2.5 on Labor Supply: Instrument, Weather and Trends (All Controls)

	(1) Baseline	(2) Inversion strength (Table 8)	(3) Weather in $t-1$ and t (Table 9)	(4) Monthly trend (Table 10)
Panel A. Second stage: ln(*monthly hours*)				
$PM_{2.5}$	-0.0149^{***}	-0.0179^{**}	-0.0212^{**}	-0.0160^{***}
	(0.0049)	(0.0088)	(0.0085)	(0.0053)
Age	0.0189^{***}	0.0189^{***}	0.0189^{***}	0.0189^{***}
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Education	0.0254^{***}	0.0253^{***}	0.0257^{***}	0.0254^{***}
	(0.0036)	(0.0036)	(0.0036)	(0.0036)
Household size	0.0265^{***}	0.0258^{***}	0.0262^{***}	0.0266^{***}
	(0.0069)	(0.0073)	(0.0071)	(0.0069)
Married	-0.2271^{***}	-0.2261^{***}	-0.2247^{***}	-0.2254^{***}
	(0.0252)	(0.0255)	(0.0255)	(0.0253)
Precipitation $(t-1)$	-0.0002	-0.0002	0.0024^{***}	0.0001
	(0.0002)	(0.0002)	(0.0009)	(0.0001)
Temperature $(t-1)$	-0.0736^{***}	-0.0881^{*}	-0.0580^{**}	-0.0688^{***}
	(0.0258)	(0.0448)	(0.0271)	(0.0247)
Wind speed $(t-1)$	-0.1024^{*}	-0.1262	0.1618^{**}	-0.0020
	(0.0614)	(0.0871)	(0.0630)	(0.0493)
Air pressure $(t-1)$	0.0359^{*}	0.0438	0.0368	0.0909^{**}
	(0.0202)	(0.0289)	(0.0242)	(0.0369)
Relative humidity $(t-1)$	0.0127^{**}	0.0155^{*}	-0.0013	0.0085^{*}
	(0.0058)	(0.0089)	(0.0040)	(0.0047)
Precipitation (t)			0.0008^{***}	
			(0.0002)	
Temperature (t)			0.0058	
			(0.0262)	
Wind speed (t)			0.2578^{*}	
			(0.1432)	
Air pressure (t)			0.2628^{**}	
			(0.1169)	
Relative humidity (t)			-0.0001	
			(0.0050)	
Months since Jan 2011 (trend)				-0.1436^{***}
				(0.0521)
Panel B. First stage: $PM_{2.5}$				
Inversion instrument	86.70^{***}	22.50^{***}	56.85^{***}	81.10^{***}
	(9.59)	(4.11)	(10.57)	(9.34)
First-stage F	81.7	29.9	28.9	75.4
Instrument	Frequency	Strength	Frequency	Frequency
Household FE	Yes	Yes	Yes	Yes
Season × Year FE	Yes	Yes	Yes	Yes
Observations	32,940	32,940	32,940	32,940
Clusters	179	179	179	179

Notes. Full set of coefficients for Tables 8–10. t is the month in which hours are worked and $t-1$ the month in which PM2.5 is measured. Each column is a separate 2SLS regression of log monthly hours on PM2.5. Column (1) is the baseline. Column (2) instruments PM2.5 by average inversion strength. Column (3) adds weather in month t. Column (4) adds a linear trend in the interview month. Panel B reports the first-stage coefficient on the instrument. All columns include household and season-by-year fixed effects. First-stage F is the cluster-robust Kleibergen–Paap F. Standard errors, in parentheses, are clustered at the thermal-inversion grid level (179 cells). $^{***}\,p<0.01$, $^{**}\,p<0.05$, $^{*}\,p<0.1$.

Table A6: Robustness of the Effect of PM2.5 on Labor Supply: Attrition, Migration and Placebo Tests (All Controls)

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	Attrition as outcome (Table 11)	Attrition as regressor (Table 11)	Excluding migrant households (Table 12)	Placebo: future (Table 13)	Placebo: random (Table 13)
$PM_{2.5}$	−0.0149***		−0.0152***	−0.0147*	−0.0081	−0.0071
	(0.0049)		(0.0050)	(0.0076)	(0.0066)	(0.0055)
Thermal inversions		−0.013			−0.135	
		(0.227)			(0.671)	
Household leaves panel next round			0.064			
			(0.048)			
Age	0.0189***	−0.0111***	0.0189***	0.0190***	0.0188***	0.0189***
	(0.0010)	(0.0017)	(0.0010)	(0.0011)	(0.0010)	(0.0010)
Age squared		0.000105***				
		(0.000020)				
Female		−0.0476***				
		(0.0043)				
Education	0.0254***	0.0054***	0.0254***	0.0224***	0.0253***	0.0255***
	(0.0036)	(0.0010)	(0.0036)	(0.0044)	(0.0036)	(0.0036)
Household size	0.0265***	0.0686***	0.0247***	0.0189**	0.0310***	0.0285***
	(0.0069)	(0.0050)	(0.0072)	(0.0088)	(0.0069)	(0.0068)
Married	−0.2271***	−0.1028***	−0.2267***	−0.1686***	−0.2349***	−0.2299***
	(0.0252)	(0.0111)	(0.0253)	(0.0293)	(0.0254)	(0.0249)
Precipitation	−0.0002	−0.0003***	−0.0001	−0.0002	0.0007***	0.0001
	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Temperature	−0.0736***	0.0409***	−0.0762***	−0.0745*	−0.0753	−0.0346
	(0.0258)	(0.0056)	(0.0271)	(0.0401)	(0.0521)	(0.0288)
Wind speed	−0.1024*	−0.0897***	−0.0978	−0.1307	−0.2077***	−0.0385
	(0.0614)	(0.0214)	(0.0598)	(0.0895)	(0.0784)	(0.0608)
Air pressure	0.0359*	0.0600***	0.0339*	0.0209	−0.0331**	0.0147
	(0.0202)	(0.0082)	(0.0198)	(0.0230)	(0.0128)	(0.0208)
Relative humidity	0.0127**	0.0070***	0.0128**	0.0094	−0.0065*	0.0053
	(0.0058)	(0.0023)	(0.0059)	(0.0082)	(0.0036)	(0.0064)
Weather measured in	Pollution month	Pollution month	Pollution month	Pollution month	Interview month	Pollution month
Mean of dep. var.		0.225				
First-stage F	81.7		77.9	34.1	84.4	52.2
Estimator	2SLS	OLS	2SLS	2SLS	2SLS	2SLS
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Season × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	32,940	22,798	32,940	23,998	32,940	32,940
Clusters	179	179	179	179	179	179

Notes. Full set of coefficients for Tables 11–13. Column (1) is the baseline. Column (2) regresses an indicator for a worker observed in 2011–12 or 2015 no longer being a member of a surveyed household in the following round on thermal inversions by OLS, with age squared and sex as additional controls. Column (3) adds an indicator for the household not being re-interviewed in the next round. Column (4) excludes households in which any member migrated between the 2011–12 and 2018–19 rounds (BIHS Module V1). Column (5) instruments PM2.5 in the interview month by inversion frequency in the interview month, controlling for the baseline instrument and interview-month weather; the thermal-inversions row in column (5) is the coefficient on the baseline instrument. Column (6) instruments PM2.5 by inversion frequency randomly reassigned across thermal-inversion grid cells within each calendar month. All columns include household and season-by-year fixed effects. Standard errors, in parentheses, are clustered at the thermal-inversion grid level (179 cells). First-stage F is the cluster-robust Kleibergen–Paap F on the excluded instrument. Households observed in only one wave are singletons under household fixed effects and drop out. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

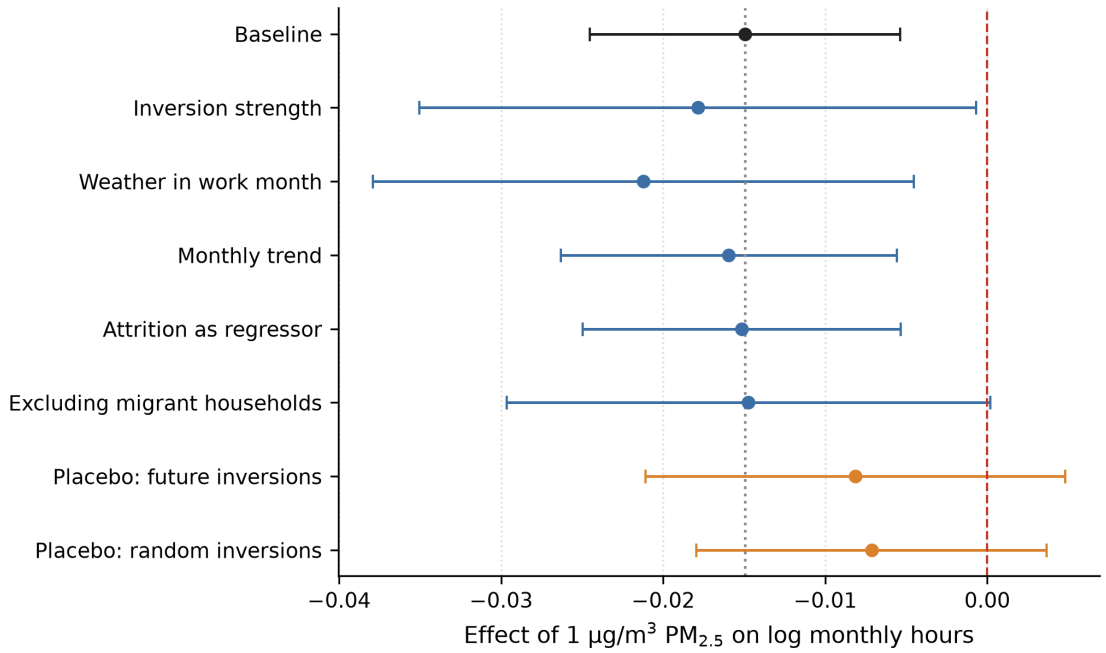


Figure A4: Robustness of the Effect of PM2.5 on Labor Supply

Note: Each marker is the 2SLS estimate of the effect of PM2.5 on log monthly hours from Tables 8–13, with 95% confidence intervals. The red dashed line is zero; the grey dotted line is the baseline estimate (−0.0149). Orange markers are placebos: one uses inversions in the interview month, after hours were worked, and the other uses inversions randomly reassigned across grid cells within each month. Standard errors are clustered at the thermal-inversion grid level.

Table A7: Pollution and the Composition of Workers

	(1) Baseline	(2) Controlling for gender	(3) Worker is female
$PM_{2.5}$	-0.0149^{***}	-0.0070^{*}	0.0056^{***}
	(0.0049)	(0.0042)	(0.0015)
Dependent variable	ln(Hours)	ln(Hours)	Female
Female indicator	No	Yes	—
Controls	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Season × Year FE	Yes	Yes	Yes
First-stage F	81.7	81.9	81.7
Observations	32,940	32,940	32,940
Clusters	179	179	179

Notes. Each column is a separate 2SLS regression on the baseline estimation sample of workers, with $PM_{2.5}$ instrumented by thermal-inversion frequency. Column (1) is the baseline estimate from Table 3. Column (2) adds an indicator for being female. Column (3) replaces the dependent variable with an indicator for the worker being female, so the coefficient measures the effect of pollution on the share of women among workers. Allowing the weather controls and season-by-year fixed effects to differ by gender yields a similar estimate to column (2) (-0.0081, s.e. 0.0043). All columns control for age, education, household size, marital status and weather in the month in which $PM_{2.5}$ is measured, and include household and season-by-year fixed effects. Standard errors, in parentheses, are clustered at the thermal-inversion grid level. First-stage F is the cluster-robust Kleibergen–Paap F on the excluded instrument. $^{***}\,p < 0.01$, $^{**}\,p < 0.05$, $^{*}\,p < 0.1$.

Table A8: Pollution, Labor Force Participation and Hours per Adult

	(1) Participation	(2) Participation	(3) Participation	(4) Monthly hours per adult
$PM_{2.5}$	0.0040**	0.0086***	0.0013	−0.463
	(0.0019)	(0.0027)	(0.0026)	(0.387)
Mean of dep. var.	0.772	0.696	0.863	85.9
Sample	All adults	Women	Men	All adults
Controls	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Season × Year FE	Yes	Yes	Yes	Yes
First-stage F	73.4	77.8	47.0	73.4
Observations	42,941	23,359	18,930	42,941
Clusters	179	179	179	179

Notes. Each column is a separate 2SLS regression on all individuals aged 15–64, whether or not they work, with $PM_{2.5}$ instrumented by thermal-inversion frequency. In columns (1)–(3) the dependent variable equals one if the individual reports any economic activity in the reference week. In column (4) the dependent variable is monthly hours worked, set to zero for individuals who do not work, so that it measures total labor supply and is not affected by changes in who works. Coefficients are per 1 $\mu g/m^3$ of $PM_{2.5}$. All columns control for age, education, household size, marital status and weather in the month in which $PM_{2.5}$ is measured, and include household and season-by-year fixed effects. Standard errors, in parentheses, are clustered at the thermal-inversion grid level. First-stage F is the cluster-robust Kleibergen–Paap F on the excluded instrument. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.