Impact of Extreme Temperatures and Air Pollution on Labor Supply and Earnings: Evidence from Vietnam

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The Impact of Extreme Temperatures and Air Pollution on Labor Supply and Earnings: Evidence from Vietnam

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Abstract
This study examines the impact of extreme temperatures and air pollution on employment in Vietnam. While we do not find significant effects of extreme temperatures or air pollution on labor force participation, we observe small but significant effects on working hours and earnings. An additional day with a mean temperature below the 5th percentile increases weekly working hours by 1.07%. Conversely, an additional day in a month with a mean temperature above the 95th percentile of the temperature distribution, compared to a day within the 5th–95th percentile range, reduces weekly working hours by 0.45% and monthly earnings by 0.71%. Air pollution has a more substantial negative impact on both working hours and earnings. When the concentration of PM2.5 increases by 1 μg/m³ over a month, it reduces weekly working hours by 1.2% and monthly earnings by 1.7%. Importantly, we find that self-employed workers are less affected by extreme temperatures and air pollution in terms of both working hours and earnings. A possible explanation is that they have greater autonomy to adjust their work schedules in response to environmental shocks. The impacts are also more pronounced among younger, skilled, and urban workers compared to older, unskilled, and rural workers. Possibly these workers are more likely to be employed in wage jobs and, compared with the self-employed, have less flexibility to adjust their work schedules in response to environmental shocks, making their total working hours more sensitive to such conditions.

Keywords
Air pollution; extreme temperatures; climate change; labor supply; employment.

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JEL Classification
J21; J23; Q54; Q53.

Original version
English

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Résumé
Cette étude examine l'impact des températures extrêmes et de la pollution de l'air sur l'emploi au Vietnam. Bien que nous ne trouvions pas d'effets significatifs des températures extrêmes ou de la pollution de l'air sur la participation à la population active, nous observons des effets faibles mais significatifs sur les heures de travail et les revenus. Une journée supplémentaire avec une température moyenne inférieure au 5ème percentile augmente les heures de travail hebdomadaires de 1,07 %. Inversement, une journée supplémentaire dans un mois avec une température moyenne supérieure au 95e centile de la distribution de température, par rapport à une journée dans la plage du 5e–95e centile, réduit les heures de travail hebdomadaires de 0,45 % et les gains mensuels de 0,71 %. La pollution de l'air a un impact négatif plus substantiel sur les heures de travail et les revenus. Lorsque la concentration de PM2,5 augmente de 1 µg/m3 sur un mois, cela réduit les heures de travail hebdomadaires de 1,2 % et les gains mensuels de 1,7 %. Il est important de noter que nous constatons que les travailleurs indépendants sont moins touchés par les températures extrêmes et la pollution de l'air en termes d'heures de travail et de revenus. Une explication possible est qu'ils ont une plus grande autonomie pour ajuster leurs horaires de travail en réponse aux chocs environnementaux. Les impacts sont également plus prononcés chez les travailleurs jeunes, qualifiés et urbains par rapport aux travailleurs âgés, non qualifiés et ruraux. Il est possible que ces travailleurs soient plus susceptibles d'occuper des emplois salariés et, par rapport aux travailleurs indépendants, qu'ils aient moins de flexibilité pour ajuster leurs horaires de travail en réponse à des chocs environnementaux, ce qui rend leur temps de travail total plus sensible à de telles conditions..

Mots-clés
Pollution de l'air ; températures extrêmes ; changement climatique ; l'offre de main-d'œuvre; emploi.

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Classification JEL
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Introduction

Extreme temperatures and air pollution are two major threats to humankind. According to a recent study conducted by Zhao et al. (2021), approximately 5 million deaths occur annually worldwide due to non-optimal temperatures. These deaths account for 9.43% of the total number of deaths, with 8.52% attributed to cold-related conditions and 0.91% attributed to heat-related conditions. A large number of studies find negative effects of extreme temperatures on health (e.g., see review from Rocque et al., 2021; Ebi et al., 2021). Moreover, heatwaves are expected to occur more frequently in the future (Meehl and Tebaldi, 2004; Tuholske et al., 2021). A warmer climate can lead to more frequent temperature inversion, which can increase surface air pollution (e.g., Caserini et al., 2017; West et al., 2023). The adverse effects of air pollution on health, particularly respiratory conditions and cardiovascular problems, have been well documented (Shah et al. 2013; Ab Manan et al., 2014; Dominski et al., 2021). Through affecting human health, extreme temperatures and air pollution can deteriorate labor supply and earnings.

Located in Southeast Asia, Vietnam is facing threats of both climate change and air pollution. Vietnam is listed among the top five countries worldwide projected to be severely affected by climate change (World Bank and Asian Development Bank. 2021). Regarding air pollution, Vietnam's levels of PM2.5 (fine particulate matter) have consistently exceeded the global average over the past two decades, reaching comparable levels to China, a country renowned for its air pollution issues (Pant et al., 2018). In this study, we examine the impact of both extreme temperatures and air pollution on labor supply and earnings in Vietnam using a very large dataset from the 2015–2022 Labor Force Surveys and daily weather and air pollution (PM2.5) data at the district level. We measure extreme temperatures by counting the number of cold and hot days, defined as days when the daily temperature falls below the 5th percentile or exceeds the 95th percentile of the district-specific daily temperature distribution over the past 20 years. To address the endogeneity of air pollution, we use an instrumental variable (IV) regression with wind directions as instruments for air pollution.

We find that while extreme temperatures and air pollution do not influence labor force participation, they significantly affect working hours and earnings of individuals aged 15 and older. Workers tend to increase working hours during months with lower temperatures and reduce working hours during months with higher temperatures. We find that an additional day with a mean temperature below the 5th percentile increases weekly working hours by 1.07%. In the context of Vietnam—a tropical country—such low temperatures are considered cool rather than cold, which may increase working hours. Conversely, an additional day in a month with a mean temperature above the 95th percentile reduces weekly working hours by 0.45%. Reduced working hours translate into lower earnings, with an additional day above the 95th percentile lowering monthly earnings by 0.71%. To assess the magnitude of the effects, we compute the elasticity of working hours with respect to cold and hot days, which are estimated at 0.012 and −0.011, respectively. These are relatively small effects, possibly due to the fact that high temperatures in Vietnam are not extremely severe. However, we find a larger negative effect of air pollution. Specifically, a 1 μg/m³ increase in the monthly PM2.5 concentration reduces weekly working hours by 1.2% and monthly earnings by 1.7%. The corresponding elasticities of working hours and earnings with respect to PM2.5 are estimated at −0.22 and −0.31, respectively.

In our heterogeneity analysis, we find that wage-earning workers are more affected by extreme temperatures and air pollution than self-employed workers. A plausible explanation is that self-employed individuals—who are typically not engaged in full-time employment—have greater flexibility to adjust their schedules. They can reduce working hours on days when they are ill or when environmental conditions are unfavorable, such as during periods of extreme heat or high air pollution, and compensate by working more on other days. In contrast, wage-earning workers, who often have fixed schedules, cannot increase working time to compensate for reduced working hours due to illness. Several qualitative studies also suggest that, compared to wage workers, self-employed individuals have greater autonomy to adjust their working time to avoid extreme temperatures (Rother et al., 2019; Schmidt, 2022; Habibi et al., 2024). This explanation is consistent with our finding that the effects of extreme temperatures and air pollution are more pronounced among formal wage workers compared to informal wage workers, and among those receiving fixed monthly salaries compared to those paid by piece rate or by time.

Compared to indoor workers, the health of outdoor workers is more directly affected by extreme temperatures and air pollution. Yet, we find that the negative effects of these environmental factors on working hours are larger for indoor workers than for outdoor workers. We argue that outdoor workers are more likely to be self-employed and therefore have greater flexibility to adjust their work schedules, resulting in their total working hours being less affected by environmental shocks. Thus, when we restrict the sample to wage-earning workers, we find that the negative effects of extreme temperatures and air pollution tend to be higher among those with high levels of outdoor exposure.

We also find that the impacts of extreme temperatures and air pollution are more pronounced among younger, skilled, and urban workers compared to older, unskilled, and rural workers. Furthermore, the effect of PM2.5 concentrations on working hours is greater in months without extreme temperatures than in months with such events. This is likely because extreme temperatures already reduce working hours and earnings, leaving less room for additional reductions caused by air pollution.

Our study makes several contributions to the literature on environmental factors affecting labor outcomes. First, it contributes to the literature on the effects of extreme temperatures on labor. Extreme temperatures lead to increased discomfort and fatigue, leading to a decline in labor productivity. A number of studies find the negative effect of high temperatures on labor productivity (e.g., Schultz et al. 2009; Deryugina and Hsiang, 2014; Adhvaryu et al., 2020; Somanathan et al., 2021; Zhao et al., 2021). Zander et al. (2015) and Somanathan et al. (2021) document that heat waves increase work absenteeism and decrease work performance of workers. While most empirical studies in the literature focus on extreme high temperatures, our study provides empirical findings on the impact of not only cold but also hot temperatures on the working time and earnings of workers in Vietnam.

Second, we contribute to the strand of literature on the impacts of air pollution. Particulate matter air pollution can decrease labor productivity at both the individual and the macro levels (Neidell, 2023). Zivin and Neidell (2012) find a negative effect of air pollution on labor productivity in agriculture in the US. Several papers find that a higher air pollution leads to a reduction in labor productivity, focusing on China (He et al., (2019), Chang et al. (2019), and Ni et al. (2023)). The impact of extreme temperatures and air pollution on labor supply and earnings remains largely unexplored in the literature. A recent study of Han et al. (2023) in South Korea finds that women with children tend to reduce working hours due to air pollution, potentially because mothers reduce their working time to take care of their children during periods of high exposure to pollution.

Thirdly, although numerous studies have examined the effects of climate change and air pollutants on health, most have studied these factors separately (Sillmann et al., 2021). Recent studies, however, highlight the importance of interaction effects of climate change and air pollution on health (e.g., Orru et al., 2017; Kalisa et al., 2018; Khajavi et al., 2019). Weather and air pollution are also strongly correlated (Jhun et al., 2015; Zhang et al., 2017; Goodenberger et al., 2024). In this study, we investigate the impact of both extreme temperatures and air pollution on labor supply and earnings in Vietnam.

This paper is structured as follows. Section 1 describes the datasets used for the analysis. Section 2 presents descriptive statistics on individual employment, temperatures and air pollution at the district level in Vietnam. Section 3 presents the methods. Section 4 presents the empirical results on the impact of extreme temperatures and air pollution on labor supply and earnings, respectively. Finally, Section 5 concludes.

1. Data sources

We use several datasets in this study. First, we use the Labor Force Surveys (LFS) from 2015 to 2022. These surveys are conducted annually by the General Statistics Office of Vietnam (GSO) and provide detailed information on employment at the individual and district levels. Each survey covers approximately 800,000 individuals across all the provinces in Vietnam, with the sample size being representative at the provincial level. The LFSs follow a two-stage stratified sampling approach. Vietnam is composed of 58 provinces, subdivided into districts, which are further divided into communes or wards. As of December 2022, there were 705 districts and 10,604 communes (GSO, 2024). The LFSs is divided into 126 strata (urban and rural areas covering 63 provinces/cities). In the first stage, a number of enumeration areas (the primary sampling units), which are villages in Vietnam, are randomly selected within each stratum using the probability proportional to size (PPS) sampling approach. In the second stage, 15 households are randomly selected within each enumeration area. It is worth noting that approximately one-twelfth of the sampled households are surveyed each month, enabling the LFS to provide monthly employment data. Sampling weights are applied to ensure that the estimates are representative of the population. The LFS collects basic demographic information for all individuals and detailed employment and wage data for people aged 15 and older. Accordingly, we use the sample of individuals aged 15 and older from the LFSs. Our study uses LFS datasets from 2015 to 2022, as they include monthly earnings data for both wage-earning and self-employed workers, whereas earlier datasets only cover wage-earning worker.

The second dataset contains weather data from weather monitoring stations, including temperature and precipitation measurements sourced from the Vietnam Institute of Meteorology, Hydrology, and Climate Change (Tran-Anh et al., 2023; Nguyen et al., 2025). It provides daily precipitation and mean temperatures collected from 481 and 147 stations across Vietnam, respectively. Weather monitoring stations are geographically evenly distributed across the country (see Nguyen et al., 2023 for the geographic map of the stations). The monitoring station data have been interpolated into a gridded dataset with a resolution of $0.1^{\circ} \times 0.1^{\circ}$ (Nguyen et al., 2025).

The third dataset includes daily PM2.5 levels, obtained from Nguyen et al. (2025). The PM2.5 data is processed using a mixed-effects model, integrating information from monitoring stations, satellite Aerosol Optical Depth (AOD) data, and meteorological and land-use variables. Ground-level PM2.5 pollution is measured at monitoring stations nationwide and subsequently modeled and predicted using satellite, meteorological, and land-use variables (Ngo et al., 2023). This approach produces daily PM2.5 data with a spatial resolution of 3 × 3 km (for more details, see Ngo et al., 2023). Additionally, we use data on other meteorological variables, such as humidity, wind speed, wind direction, surface pressure, and thermal inversion, also sourced from Nguyen et al. (2025).

The meteorological and air pollution datasets are gridded and aligned with district boundaries. We merge individual-level data on employment from the LFSs with meteorological and air pollution data at the district level.

2. Descriptive statistics

2.1. Employment

Table 1 presents summary statistics on the employment of individuals aged 15 and older in Vietnam, based on LFS data from 2015 to 2022. Table A.1 in the Appendix present the main characteristics of individuals in the datasets. Vietnam has traditionally maintained a relatively high labor force participation rate, though it has declined in recent years, falling from 75.8% in 2015 to 72.9% in 2022. The table also provides estimates of the proportion of working people and the proportion of people with self-employment and wage-earning jobs. These proportions are computed over the total adult population aged 15 and older. The employment rate decreased from 74.6% in 2015 to 71.8% in 2022. Vietnam has a low unemployment rate due to the substantial size of self-employed workers. In 2022, 35.8% of individuals aged 15 and older were employed in wage jobs, while 36.0% were self-employed. The labor force participation and the employment rate were lower in 2021, when social distancing measures were in place to contain the COVID-19 pandemic.

Table 1 also presents estimate of the working hours and earnings of employed individuals aged 15 and older. The average number of working hours during the past 7 days declined slightly from 43.8 hours in 2015 to 41.1 hours in 2022. In this study, we examine the effects of extreme temperatures and air pollution on both self-employed and wage-earning workers. Wage-earning workers tend to have more weekly working hours than self-employed individuals. In 2022, wage-earning workers reported an average of 46.2 working hours in the past week, compared to 36.1 hours for self-employed workers. Wage-earning workers also have higher monthly earnings. In 2022, their average monthly earnings were 7,663 thousand VND, compared to 7,497 thousand VND for self-employed workers.

2.2. Extreme temperatures

Vietnam is a tropical country divided into six geographic regions. The three northern regions experience four distinct seasons, while the three southern regions have two seasons: dry and rainy. In Figure 1, we compute the average temperature across days and districts for each region during the 2012-2022 period. The average temperature was slightly higher in 2015 and 2019.

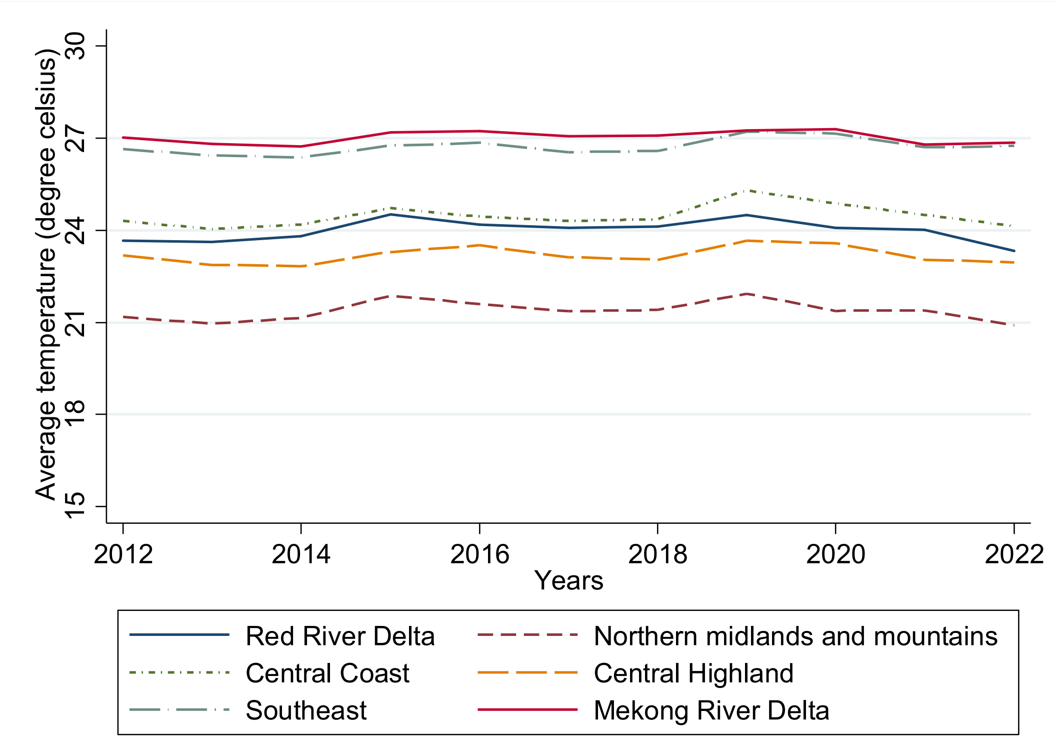
Table 1. Employment outcomes

Employment variables	Year 2015	Year 2016	Year 2017	Year 2018	Year 2019	Year 2020	Year 2021	Year 2022
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Labor force participation rate (%)	75.8	76.1	76.3	76.3	76.2	73.4	66.7	72.9
	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.4)	(0.4)
Proportion of employed people (%)	74.6	75.1	74.7	74.7	74.7	71.7	65.3	71.8
	(0.3)	(0.4)	(0.3)	(0.3)	(0.3)	(0.4)	(0.4)	(0.4)
Proportion of people having a wage job (%)	30.1	31.5	32.0	32.8	35.5	34.9	33.9	35.8
	(0.5)	(0.5)	(0.4)	(0.4)	(0.5)	(0.6)	(0.5)	(0.5)
Proportion of people having a self-employed work (%)	44.5	43.6	42.7	41.9	39.2	36.8	31.4	36.0
	(0.7)	(0.7)	(0.5)	(0.5)	(0.6)	(0.6)	(0.6)	(0.6)
Number of working hours in the past 7 days of all workers	43.8	43.9	42.9	44.2	42.3	42.3	42.6	41.1
	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)
Number of working hours in the past 7 days of self-employed workers	41.6	41.5	40.6	41.9	38.2	38.8	38.6	36.1
	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.3)	(0.3)
Number of working hours in the past 7 days of wage-earning workers	47.1	47.3	46.0	47.2	46.7	45.9	46.4	46.2
	(0.2)	(0.2)	(0.1)	(0.2)	(0.2)	(0.1)	(0.1)	(0.1)
Earnings during the past month of workers (thousand VND)	5520.6	5803.5	6061.2	6357.6	6943.2	6901.0	7096.6	7597.6
	(74.6)	(81.5)	(68.8)	(73.0)	(89.8)	(80.0)	(75.1)	(76.4)
Earnings during the past month of self-employed workers (thousand VND)	5115.3	5411.2	5708.2	6039.3	6389.6	6415.3	7000.1	7497.2
	(89.8)	(94.6)	(89.4)	(99.9)	(110.0)	(91.3)	(107.5)	(110.0)
Earnings during the past month of wage-earning workers (thousand VND)	5979.0	6213.9	6415.8	6665.9	7414.5	7295.1	7164.0	7663.5
	(73.5)	(82.1)	(68.9)	(65.2)	(88.2)	(81.3)	(75.4)	(75.7)

Note: The sample includes employed people aged from 15.
Wage and income are measured in December 2022 prices (adjusted by monthly overall CPI)
The standard errors of the means in parentheses.
Source: Estimation using data from the LFSs 2015-2022.

By regions, the Northern midlands and mountain areas have the lowest average temperature at 21°C, whereas the Southeast and Mekong River Delta are the hottest regions, with an average temperature of around 27°C. Figures A.1 and A.2 presents the box plot and scatter plot of daily temperatures across months. For Northern regions (Northern midlands and mountain areas, Red River Delta, and North Central and Central coastal areas) the temperature was highest in May to June and lowest in January and December. On the other hand, the temperature in Southern regions (Central Highlands, Southeast, and Mekong River Delta) are quite stable over months.

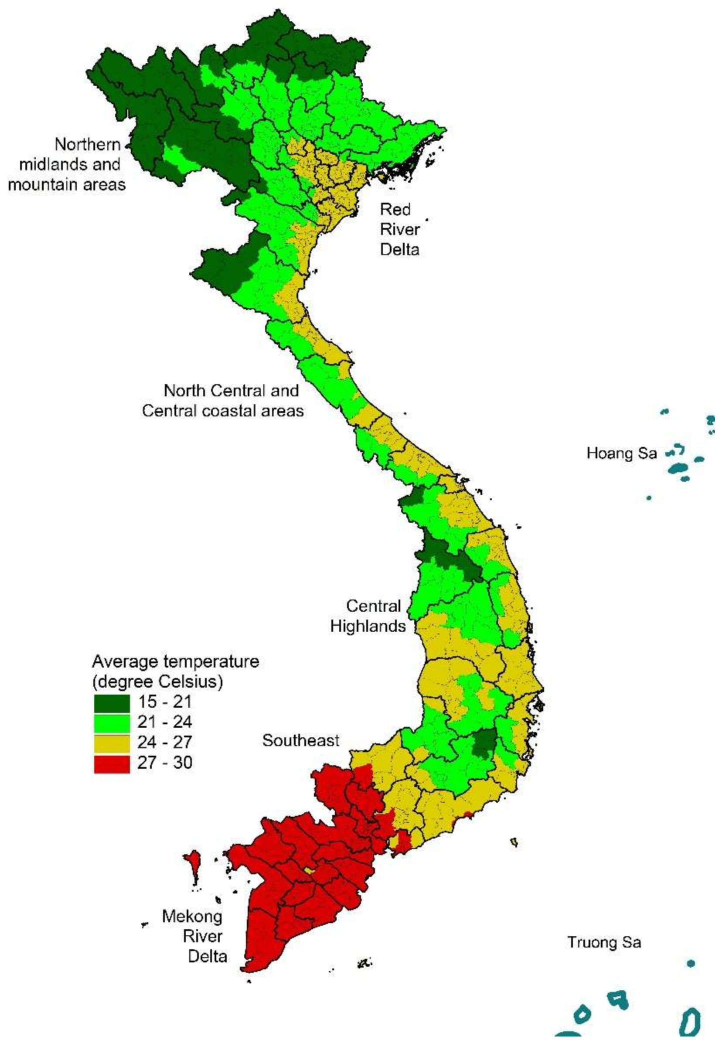
Figure 1: Average daily temperature over time



Note: This figure presents the average daily temperature, which is averaged across districts during the 2012-2022 period.

We merge individual data from the LFSs with meteorological and air pollution data at the district level, assigning the same meteorological and air pollution values to all individuals within each district. Figure 2 shows the average daily temperature at the district level from 2015 to 2022. It should be note that Figure 2 shows long-term averages, which smooth out short-term fluctuations

Figure 2: The average daily temperature during the 2015-2022 period



Source: Authors' preparation using data on the daily mean temperature of each district averaged over the 2015–2022 period.

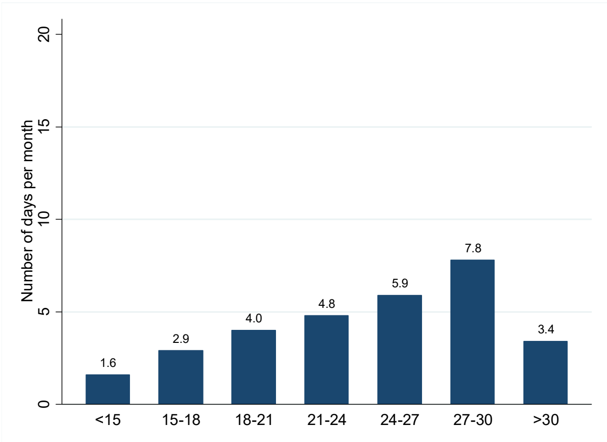
Following prior studies such as Deschenes and Greenstone (2011), Barreca et al. (2016), Deryugina and Hsiang (2017), and Mullins and White (2020), we classify days within a month into temperature bins to capture the non-linear relationship between temperature and employment. For example, the impact may be minimal between 25°C and 30°C, but much stronger between 30°C and 35°C due to sharp declines in productivity caused by extreme heat. According to WHO (2018b), temperatures between 15°C and 30°C are considered unlikely to have adverse health effects. Since days with temperatures below 15°C or above 30°C are relatively rare in Vietnam, we construct seven temperature bins (in degrees Celsius) as follows: 0–15, 15–18, 18–21, 21–24, 24–27, 27–30, and 30+. For each district, we calculate the number of days within these temperature bins for each month. Figure 3 shows the average number of days in each temperature bin, averaged across districts and months during the 2015–2022 period. The results indicate that the Northern Midlands and Mountain areas have the highest number of days with temperatures below 15°C, followed by the Red River Delta and the North Central and Central Coastal regions. Although the Red River Delta has a lower average temperature than the southern regions, it records the highest average number of days with temperatures above 30°C.

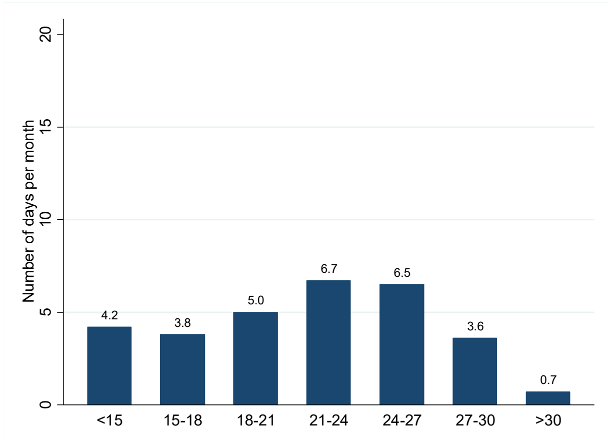
People can adapt to low or high temperatures in their local environment (e.g., Anderson and Bell, 2009; Kent et al., 2014; Tochihara et al., 2022). As a result, using common or absolute temperature thresholds may not be appropriate in a country with varying climates. The impact of a 30°C temperature may be more pronounced in colder regions as opposed to warmer ones. For instance, temperatures in the 27–30°C range are normal for residents of hotter regions such as the Southeast and Mekong River Delta but are considered relatively high for those in cooler areas like the Northern Midlands and Mountain regions or the Central Highlands. To measure the causal effects of temperature shocks, we define a cold day in a district as one where the daily temperature falls below the 5th percentile of the district-specific daily temperature distribution over the past 20 years. Similarly, a hot day is defined as a day with a temperature exceeding the 95th percentile of the district's temperature distribution. These temperature extremes deviate significantly from the long-term average and are more likely to be unexpected by local residents.

Figure 3: The average number of days per month by temperature bins, 2015-2022

Panel A. Red River Delta

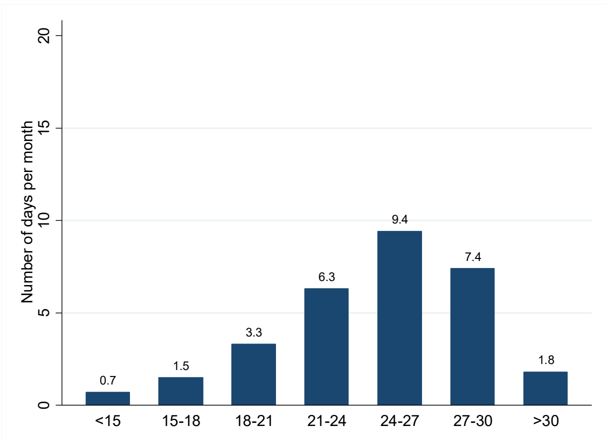
Panel B. Northern midlands and mountain areas

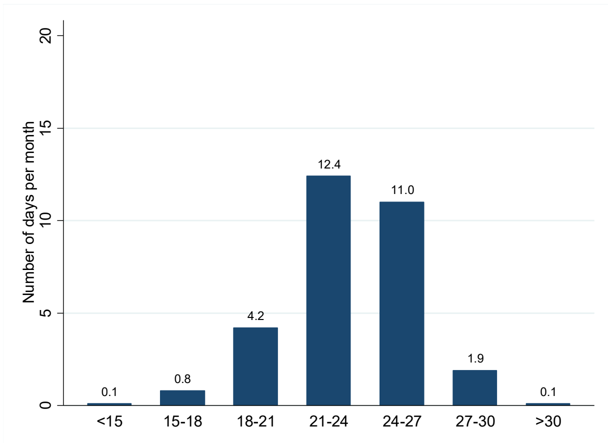




Panel C. North Central and Central coastal areas

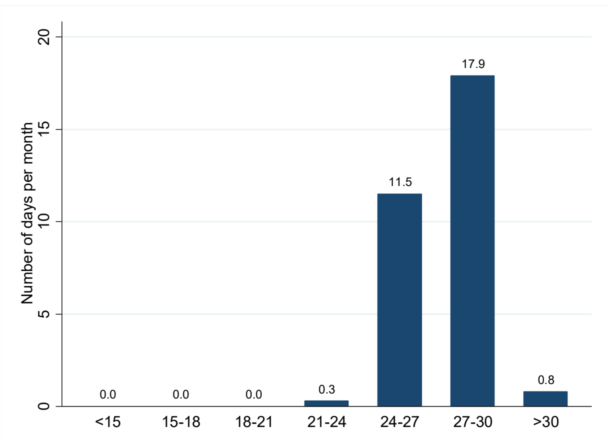
Panel D. Central Highlands

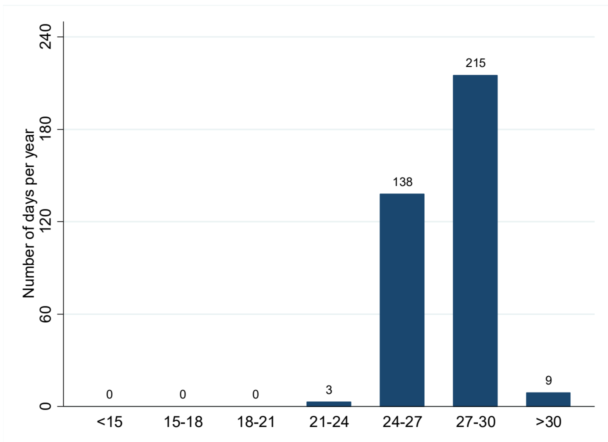




Panel E. Southeast

Panel F. Mekong River Delta





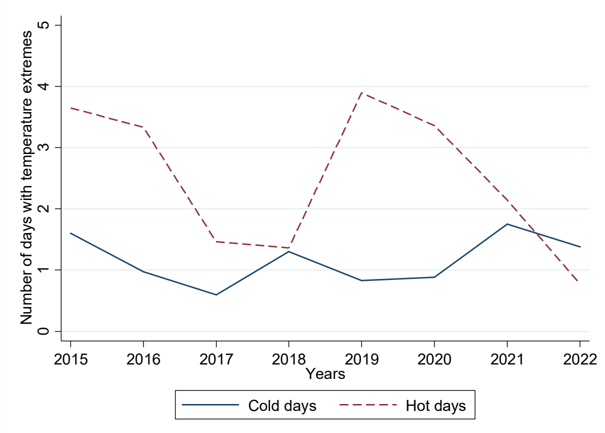
Note: This figure presents the average number of days per month, with daily mean temperatures falling into 7 bins for the 2015-2022 period. The figure presents the temperature distribution for 6 regions.

Panel A of Figure 4 shows the average number of days below the 5th percentile (referred to as "cold days") and above the 95th percentile (referred to as "hot days") of the district-specific daily temperature distribution over the past 20 years. We compute the number of hot and cold days for each month and district, and Panel A presents these values averaged across months and districts. The figure indicates that the number of hot days exceeded the number of cold days during the 2015–2022 period, reflecting the rising temperatures in recent years.

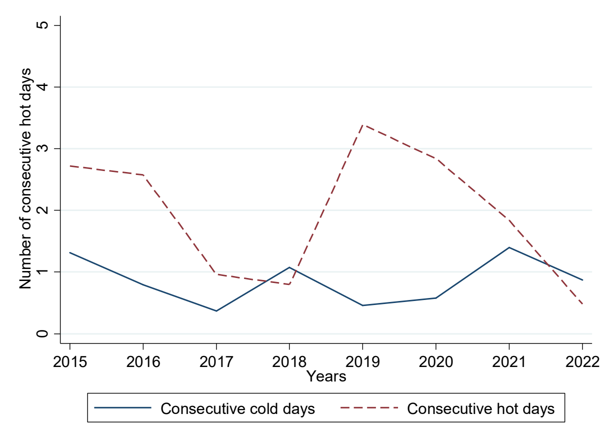
The number of cold and hot days within a month does not account for the duration of these extremes. Longer cold and heat waves cause more severe health impacts. For Vietnam, Nguyen et al. (2023) found that extended cold and heat waves have a greater effect on mortality than shorter ones. Cold and heat waves are typically defined as prolonged periods of abnormally low or high temperatures (e.g., Perkins and Alexander, 2013; Dimitrova et al., 2021). We define a cold wave in a district for a given month as occurring when there are three or more consecutive days with a daily mean temperature below the 5th percentile of the district-specific daily temperature distribution over the past 20 years. Similarly, a heat wave is defined as three or more consecutive days with a daily mean temperature above the 95th percentile of the district-specific temperature distribution. To further investigate the impact of duration, we also define cold and heat waves using longer thresholds of at least 5 and 7 consecutive days to examine whether extended durations of these extremes have more pronounced negative effects on employment. Panels B, C, and D of Figure 4 present the number of days in cold and heat waves per month, using thresholds of 3, 5, and 7 consecutive days, respectively. The overall pattern of cold and heat waves over time remains consistent across different duration thresholds. The frequency of cold and heat waves decreases as the duration threshold increases.

Figure 4: The average number of days with extreme temperatures during a month

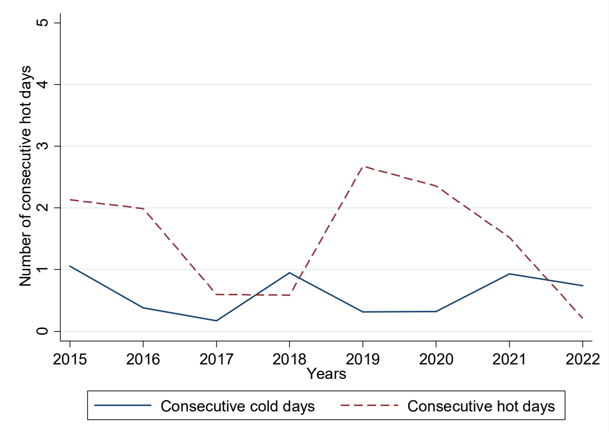
Panel A. The average number of cold and hot days



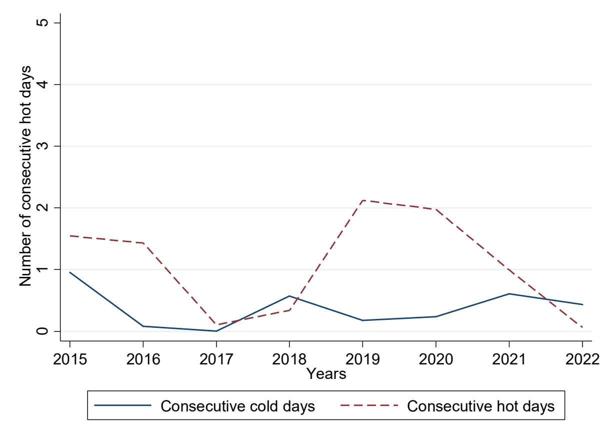
Panel B. The average number of consecutive days in 3-day cold and heat waves



Panel C. The average number of consecutive days in 5-day cold and heat waves



Panel D. The average number of consecutive days in 7-day cold and heat waves

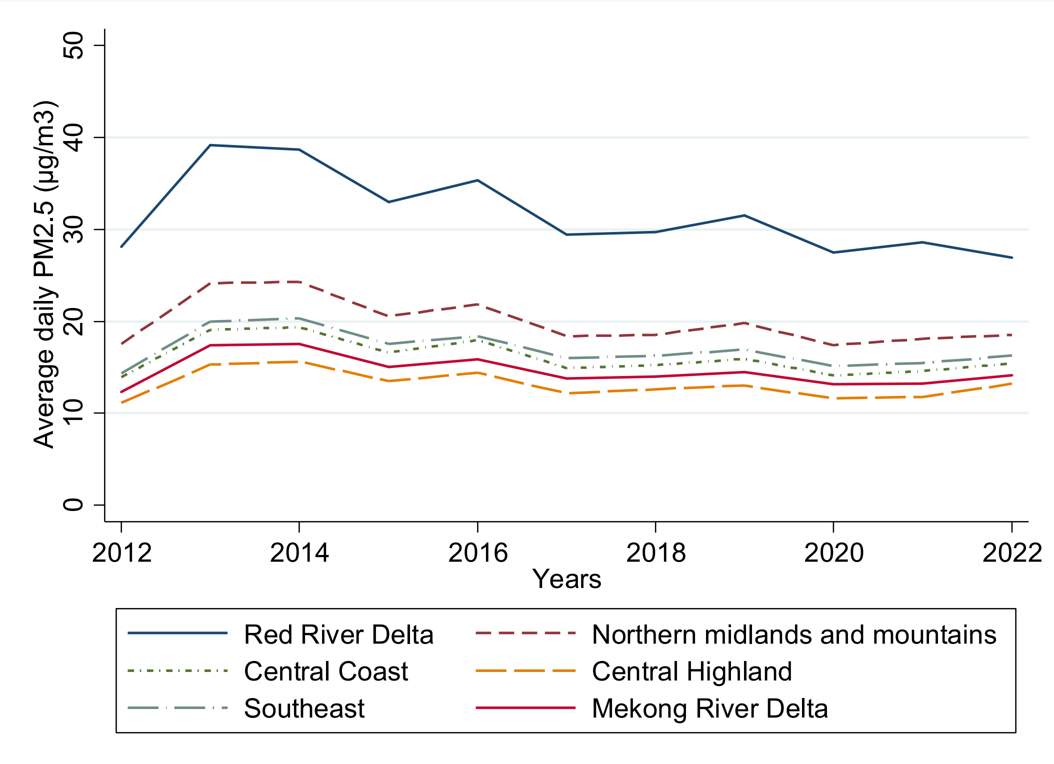


Note: The cold and hot days are defined based on the 5th and 95th percentiles of the district-specific daily temperature distribution during the past 20 years.

2.3. Air pollution

Vietnam is among the most air-polluted countries (Pant et al., 2018; Wolf et al., 2024). In 2024, Vietnam ranked 166th out of 180 countries in term of air quality (Block et al., 2024).[1] We compute daily PM2.5 levels for each district. Figure 5 displays the average district-level daily PM2.5 concentrations during the 2015–2022 period. It shows that the average PM2.5 slightly decreased during this period. Red River Delta has substantially higher PM2.5 than other regions. Central Highlands is the region with the lowest PM2.5.

Figure 5: The average daily PM2.5 over time

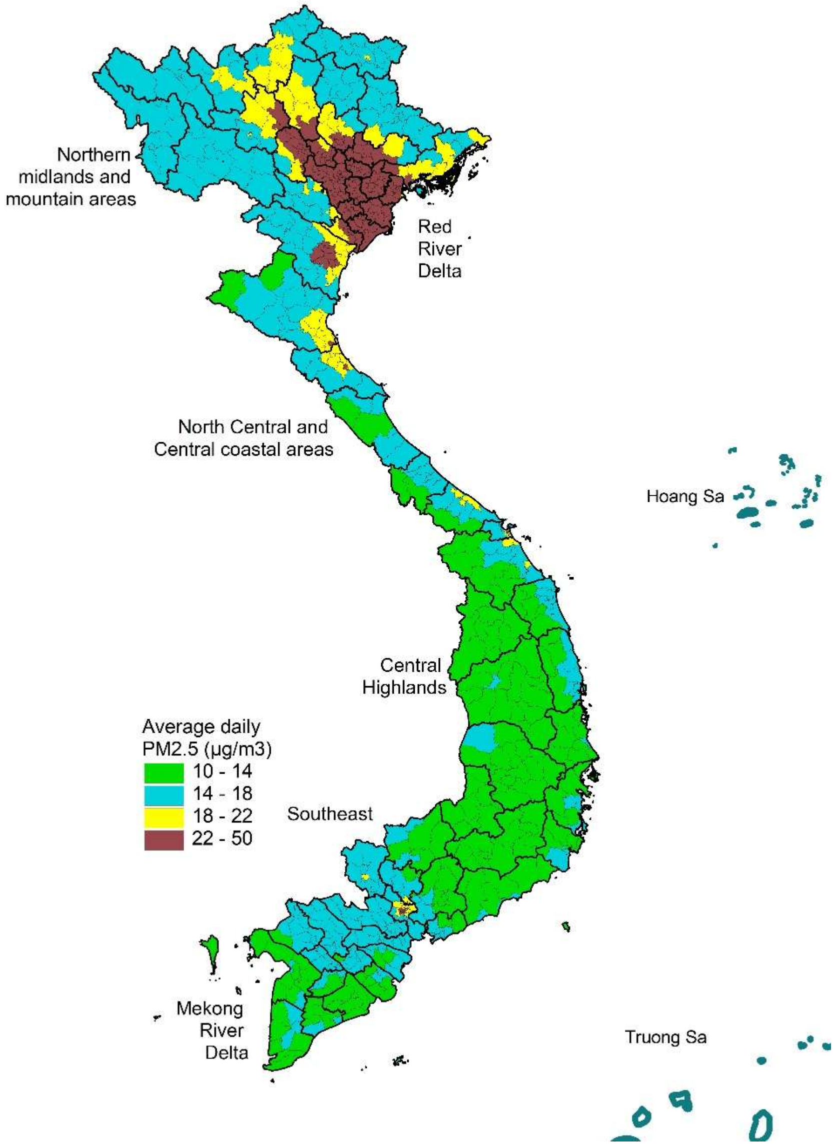


Note: This figure presents the average daily PM2.5 ($\mu g/m^3$) which is averaged across districts during the 2012-2022 period.

[1] In this study, the air quality index is measured using an aggregate indicator constructed from various components, including PM2.5, household solid fuel use, ozone exposure, NO_2, SO_2, CO, and VOC exposure (for more details, see Block et al., 2024).

Figure 6 shows a district-level map of the average daily PM2.5 levels for the 2015–2022 period. The variation in average daily PM2.5 levels across districts within the same region is minimal. PM2.5 emissions are more concentrated in delta areas, as shown on the map. Areas such as Hanoi and its surroundings, as well as Ho Chi Minh City, are marked in brown, indicating the highest concentrations of PM2.5.

Figure 6: The average daily PM2.5 of districts



Source: Authors' preparation using the daily PM2.5 of districts averaged over the 20015–2022 period.

3. Estimation method

In this study, we estimate the effects of extreme temperatures and air pollution on labor supply and earnings. We perform regressions of individual-level outcomes on exposure to extreme temperatures and air pollution at the district level and other control variables including geographic and time fixed effects. We first begin with the regression of working hours and earnings on temperature bins and PM2.5 as follows:

$$y_{idmt} = \alpha_1 + \sum_{j=1}^{k} \beta_{1j} Temp_{dmt} + \gamma_1 PM25_{dmt} + X_{idmt}\theta_1 + D_d + T_t + M_m + e_{idmt}, \quad (1)$$

where y_{idmt} denotes a dependent variable of individual *i* in district *d* in month *m* in year *t*. The dependent variables include log of working hours during the past 7 days and log of monthly earnings. $Temp_{dmt}$ denotes variables indicating the number of days with the daily mean temperature falling in specific bins in district *d*, during month *m* of year *t*. $PM25_{dmt}$ is the average PM2.5 (μg/m³) in district *d* in month *m* of year *t*. X_{idmt} denotes control variables including both individual-level and district-level variables. The control variables should be exogenous are not affected by the main explanatory variables of interest, i.e., temperature and air pollution in this study (Heckman et al., 1999). We control for a small, but relevant number of individual-level variables including age, age squared, gender, a dummy indicating Kinh ethnic group, and urban dummy of individuals. There are 54 ethnic groups in Vietnam, in which Kinh group accounts for 85% of the total population. District-level control variables include monthly precipitation, wind speed, air pressure, thermal inversion, and humidity. We also control for district fixed-effects D_d and year fixed-effects T_t, month fixed effects M_m.[2]

As mentioned, we classify days within a month into different temperature bins in degrees Celsius as follows: 0–15°C, 15–18°C, 18–21°C, 21–24°C, 24–27°C, 27–30°C, and 30°C+.According to the WHO (WHO, 1990), temperature ranges that are most comfortable for people are from 18°C to 24°C. Thus, we use the 21–24°C bin as the reference. The effect of this temperature bin on employment is assumed to be zero.

In a second model, we analyze exceptional temperature events as exogenous shocks (particularly cold or hot days) rather than considering only daily temperatures, as local population can adapt to temperatures over time in a given area. As mentioned in the previous section, we define the extreme temperatures that a district is exposed to by the number of days within a month which are below the 5th percentile (cold days) or above 95th percentile (hot days) of the temperature distribution of a district during the past 20 years. Our second regression model is depicted as follows:

$$y_{idmt} = \alpha_2 + \beta_{21} Low\_Temp_{dmt} + \beta_{22} High\_Temp_{dmt} + \gamma_2 PM25_{dmt} + X_{idmt}\theta_2$$
$$+ D_d + T_t + M_m + u_{idmt}, \quad (2)$$

[2] There has been recent concern about bias in fixed-effects regression due to treatment effect heterogeneity (e.g., Roth et al., 2023). Current methods addressing this issue are often designed for binary treatment outcomes and require the presence of untreated or not-yet-treated units, which are not applicable in the context of temperature and air pollution.

where Low_Temp_{dmt} and $High\_Temp_{dmt}$ are the number of cold and hot days in district *d* during month *m* of year *t*, respectively. Similarly, we also measure the extreme temperatures by the number of consecutive days in the cold and heat waves that happen in district *d* during month *m* of year *t.*

While extreme temperatures are more exogenous, air pollution is not. High population density and areas with more concentration of factories are more likely to have higher air pollution. Individuals in these areas can also have higher labor supply and earnings. As a result, estimates of the air pollution on labor supply and earnings may be underestimated due to selection bias. A common method to estimate the impact of air pollution is instrumental variable regression. Thermal or temperature inversions (Arceo et al., 2016; He et al., 2019; Deschenes et al., 2020; Chen et al., 2022; Xie et al., 2023) and wind patterns, particularly wind directions (e.g., Deryugina et al., 2019; Rangel and Vogl, 2019; Isphording and Pestel, 2021; Li and Meng, 2023; Austin et al., 2023), are commonly used as instrumental variables for air pollution. However, thermal inversions may themselves be endogenous due to the urban heat island effect (e.g., Santamouris et al., 2011; Rendón et al., 2014). The characteristics of urban infrastructure result in greater absorption of solar radiation, leading to higher temperatures and more frequent thermal inversions compared to rural areas (e.g., Santamouris et al., 2011; Rendón et al., 2014; Li and Chao, 2018; Khalesi et al., 2020). We use wind directions as the instrumental variable for PM2.5. Following previous studies (Deryugina et al., 2019; Rangel and Vogl, 2019; Isphording and Pestel, 2021; Li and Meng, 2023; Austin et al., 2023), we construct binary variables indicating wind direction bins: [0, 45) and [45, 90) degrees for the east; [90, 135) and [135, 180) degrees for the south; [180, 225) and [225, 270) degrees for the west; and [270, 315) and [315, 360) degrees for the north. These instrumental variables allow us to avoid controlling for the sources of air pollution (Deryugina et al., 2019).

There are two main conditions for a valid instrumental variable. The relevance condition requires that the instrument is correlated with the endogenous variable. As we will see in the next section, wind direction is strongly correlated with PM2.5. The exclusion restriction requires that the instrument is uncorrelated with the error term in the labor equation. Given that we have control for wind speed, thermal inversion and other meteorological variables, as well as district and time fixed effects, we expect the wind directions to be exogenous.

It should be noted that we are unable to estimate the non-linear effects of monthly PM2.5 or the distributional effects of daily PM2.5 (such as PM2.5 bins analogous to temperature bins) as we cannot construct instrumental variables from wind directions to capture these non-linear effects.

Since our main variables of interest—extreme temperatures and PM2.5—are measured at the district level, we cluster the standard errors at the district level. For robustness checks, we also cluster the standard errors at the primary sampling unit (enumeration areas) and use traditional heteroskedasticity-consistent standard errors as an alternative approach.

The models specified in equations (1) and (2) are used to estimate the short-term effects of extreme temperatures and air pollution on working time and earnings among employed individuals. In addition, we also examine whether extreme temperatures and air pollution can influence labor force participation, employment, wage jobs, and self-employment (the outcome variables shown in Table 1). We apply similar models as equations (1) and (2). However, we measure temperature bins and extreme temperatures by the number of days in different bins and the number of cold and hot days over the past 12 months, rather than the current month. Air pollution is also measured by the average PM2.5 concentration during the same 12-month period instead of the current month.

4. Empirical results

4.1. Impacts on working hours and earnings

We begin with estimating of the impact of temperature bins and PM2.5 on working hours during the past days and earning during the past month using the 2SLS regression specified in equation (1). The instrumental variables used for PM2.5 are the wind directions. The first-stage regression of PM2.5 are presented in Table A.2 in the Appendix. There is a strong correlation between the wind direction variables and PM2.5. Both the Cragg-Donald Wald *F* statistics and effective *F* statistics are very high, indicating the strength of the IVs (Staiger and Stock, 1997; Olea & Pflueger, 2013).[3]

We plot the coefficients of temperature bins from the 2SLS regressions of the logarithm of weekly working hours and monthly earnings. The full regression results are presented in Appendix Table A.3. For comparison, fixed-effects regression results are also included in the same table, but our interpretation focuses on the 2SLS results.[4] Panel A of Figure 7 shows that people tend to work longer hours in cooler months. The coefficient for the number of days below 15°C is positive but not statistically significant. An additional day with a daily mean

[3] As a rule of thumb, instrumental variables might be weak if the Cragg-Donald Wald *F* test value is below 10 (Staiger & Stock, 1997) or the effective F test value is less than 37.42 (Olea & Pflueger, 2013).

[4] Significance levels of 1%, 5%, and 10% are indicated with star markers in all regression tables. However, to minimize the risk of Type I error, we interpret only results that are significant at the 1% or 5% levels.

temperature in the 15–18°C bin or the 18–21°C bin is associated with a 0.14% or 0.1% increase in working hours over the past 7 days, respectively, compared to a reference day with a temperature of 21–24°C. Conversely, workers tend to work fewer hours in months with more days of higher temperatures. An additional day with a daily mean temperature exceeding 30°C, compared to a reference day with a temperature of 21–24°C, is associated with a 0.94% reduction in working hours over the past seven days (column 1). Reduced working hours lead to lower earnings. Panel B of Figure 7 shows that monthly earnings also decline in months with more days hotter than 30°C. Specifically, an additional day with a daily mean temperature over 30°C, relative to a reference day of 21–24°C, is associated with a 0.98% decrease in monthly income.

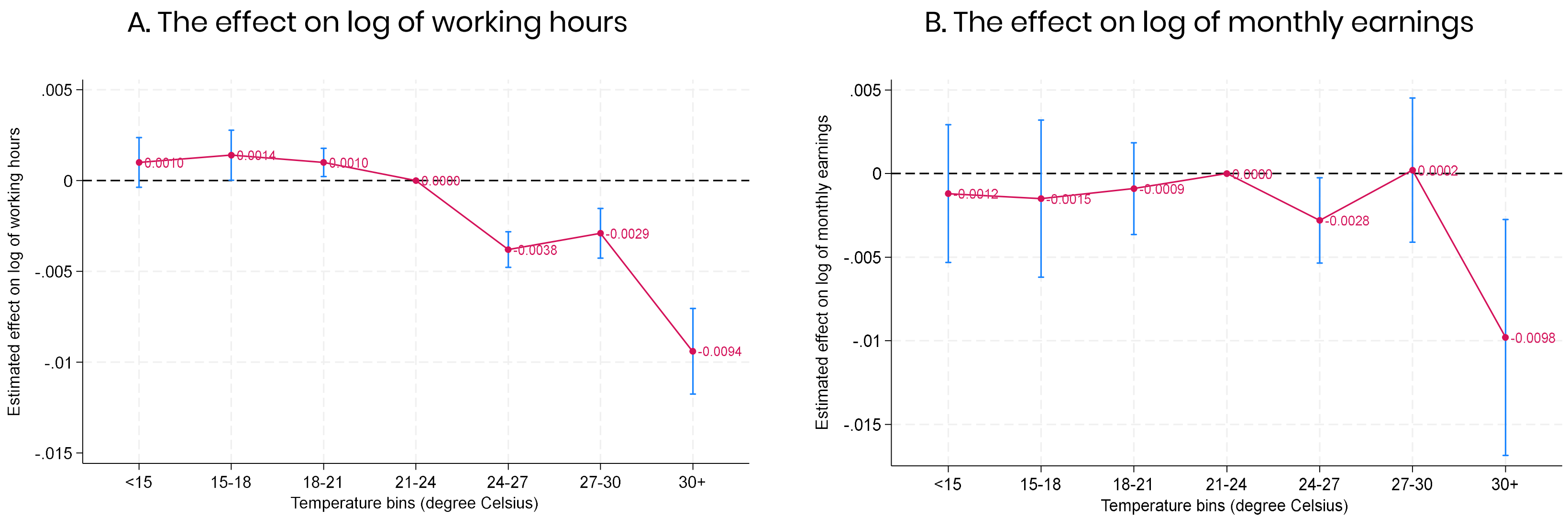
Tables 2 and 3 present 2SLS regression results of working hours and monthly earnings on PM2.5, extreme temperatures, and other control variables. For comparison, fixed-effects regression results are provided in Tables A.4 and A.5 in the Appendix. Overall, the effects of extreme temperatures on working hours and earnings are consistent with the associations observed between temperature bins and these outcomes.

Table 2 demonstrates that cooler days increase work hours, while hot days reduce working hours. An additional day (in a month) with a mean temperature below the 5th percentile increases weekly working hours by 1.07%. Vietnam is a tropical country, and the low temperature extremes are not very cold. This explains why low temperatures can have a positive effect on working hours. While cold days have a positive effect on earnings, this effect is not statistically significant at conventional levels. Conversely, an additional day (in a month) with a mean temperature above the 95th percentile of the temperature distribution, compared to a day within the 5th–95th percentile range, decreases weekly working hours by 0.45% and monthly earnings by 0.71%.

To assess the magnitude of the effect of extreme temperatures, we calculate the elasticity of working hours with respect to the number of cold and hot days. During the 2015–2022 period, the average number of cold and hot days per month was 1.16 and 2.50, respectively (Figure 4 – Panel A). An additional cold day represents 86.2% of the average number of cold days per month, while an additional hot day corresponds to 40% of the average number of hot days. This implies that a 1.07% increase in working hours results from an 86% increase in the number of cold days, yielding an elasticity of working hours to cold days of 0.012 (1.07% divided by 86%). Similarly, the elasticity of working hours to hot days is -0.011 (-0.45% divided by 40%), and the elasticity of monthly earnings to hot days is -0.018 (-0.71% divided by 40%). This effect is relatively small, possibly because high temperatures in Vietnam are not as extreme as those in several African and Middle Eastern countries.

In Table 3, we estimate the effect of cold waves and heat waves on working hours and earnings. A cold/wave is defined on at least 3 consecutive cold/hot days. Appendix Tables A.6 and A.7 present the estimates of the impact of cold/heat waves with longer durations of at least 5 and 7 consecutive cold days, respectively. Overall, the results in these Tables are similar to those in Table 3. According to Table 3, an additional day of a cold wave with at least 3 consecutive cold days increases weekly working hours by 1.21%, while an additional day of a heat wave at least 3 consecutive hot days reduces weekly working hours by 0.38%. A heat wave also decreases monthly earnings: additional hot days in a heat wave reduces monthly earning by 0.62%.

Figure 7: The effect of temperature bins on working hours and earnings



Note: This figure displays the estimates and their 95% confidence intervals for the effect of temperature bins on the logarithm of working hours and monthly earnings of employed individuals aged 15 and above, based on 2SLS regressions. The model specification is outlined in equation (1).

Table 2. 2SLS regression of working hours and earnings on extreme temperatures and PM2.5

Explanatory variables	All workers		Self-employed workers		Wage-earning workers	
	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings
	(1)	(2)	(3)	(4)	(5)	(6)
PM 2.5 (μg/m3)	-0.0115***	-0.0172***	-0.0086***	-0.0146**	-0.0144***	-0.0119***
	(0.0018)	(0.0043)	(0.0021)	(0.0068)	(0.0019)	(0.0022)
Number of days below the 5th temperature percentile	0.0107***	0.0018	0.0087***	0.0008	0.0130***	0.0020*
	(0.0011)	(0.0023)	(0.0010)	(0.0032)	(0.0014)	(0.0012)
Number of days above the 95th temperature percentile	-0.0045***	-0.0071***	-0.0030***	-0.0088***	-0.0062***	-0.0060***
	(0.0005)	(0.0011)	(0.0004)	(0.0016)	(0.0007)	(0.0008)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.0974***	-6.6956**	5.7778***	-2.7132	0.6745	-0.7137
	(1.1309)	(2.9951)	(1.3363)	(4.7800)	(1.3471)	(1.5372)
Observations	3,583,824	3,583,824	2,053,021	2,053,021	1,530,803	1,530,803

Note: This table reports 2SLS regression of working hours and earnings on PM2.5, temperature variables, and other control variables. The instrumental variable for PM2.5 is wind direction dummies. Individual-level control variables include age, age squared, gender, education level dummies, and urban dummy of individuals. District-level control variables include monthly precipitation, wind speed, air pressure, thermal inversion, and humidity.
Robust standard errors in parentheses. The standard errors are clustered at the district level.
*** p<0.01, ** p<0.05, * p<0.1.

Table 3. 2SLS regression of working hours and earnings on cold/heat waves and PM2.5

Explanatory variables	All workers		Self-employed workers		Wage-earning workers	
	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings
	(1)	(2)	(3)	(4)	(5)	(6)
PM 2.5 (μg/m3)	-0.0109***	-0.0165***	-0.0082***	-0.0138**	-0.0136***	-0.0111***
	(0.0017)	(0.0042)	(0.0020)	(0.0066)	(0.0018)	(0.0021)
Number of days with at least 3 consecutive days below the 5^{th} temperature percentile	0.0121***	0.0037	0.0096***	0.0022	0.0153***	0.0040***
	(0.0011)	(0.0023)	(0.0010)	(0.0031)	(0.0015)	(0.0013)
Number of days with at least 3 consecutive days above the 95^{th} temperature percentile	-0.0038***	-0.0062***	-0.0026***	-0.0077***	-0.0052***	-0.0056***
	(0.0004)	(0.0011)	(0.0004)	(0.0015)	(0.0006)	(0.0007)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.8470**	-6.9678**	5.5788***	-3.1612	0.3394	-0.5905
	(1.1343)	(3.0176)	(1.3386)	(4.8090)	(1.3512)	(1.5444)
Observations	3,583,824	3,583,824	2,053,021	2,053,021	1,530,803	1,530,803

Note: This table reports 2SLS regression of working hours and earnings on PM2.5, temperature variables, and other control variables. The instrumental variable for PM2.5 is wind direction dummies. Individual-level control variables include age, age squared, gender, education level dummies, and urban dummy of individuals. District-level control variables include monthly precipitation, wind speed, air pressure, thermal inversion, and humidity. Robust standard errors in parentheses. The standard errors are clustered at the district level.
*** p<0.01, ** p<0.05, * p<0.1.

With respect to air pollution, we observe a negative effect of PM2.5 concentration on both weekly working hours and monthly earnings. Tables 2 and 3 provide very similar estimates for the impact of air pollution. For interpretation, we rely on the results from Table 2. It shows that a 1 μg/m³ increase in the monthly concentration of PM2.5 reduces weekly working hours by 1.2% and monthly earnings by 1.7%. During the 2015–2022 period, the average PM2.5 concentration across districts and months was 18.5 μg/m³, and 1 μg/m³ represents 5.4% of this average. Using this figure, we can roughly calculate the elasticity of working hours and monthly earnings with respect to PM2.5 as -0.22 and -0.31, respectively. These values suggest that the responsiveness of labor outcomes to air pollution is significantly greater than to extreme temperatures. This may be because air pollution in Vietnam is more severe than temperature extremes.

In Tables 2 and 3, we estimate the impact of extreme temperatures separately for self-employed workers and wage-earning workers. Since selection into employment types is not exogenous, there may be sample selection bias. Thus, we assume that employment type is predetermined and focus solely on the short-term effects of extreme temperatures and air pollution on working hours and earnings. We find that extreme temperatures and air pollution have a negative impact on both groups. An additional cold day increases working hours by 0.87% for self-employed workers and by 1.30% for wage-earning workers (columns 3 and 5 of Table 2). Conversely, an additional hot day reduces working hours by 0.30% for self-employed workers and by 0.62% for wage-earning workers (columns 4 and 6 of Table 2). High-temperature extremes also result in a decline in earnings for both groups. Both self-employed and wage-earning workers tend to reduce their working hours during months with high levels of air pollution. A 1 μg/m³ increase in the monthly concentration of PM2.5 reduces weekly working hours by 0.86% for self-employed workers and by 1.44% for wage-earning workers (columns 3 and 5 of Table 2). Monthly earnings for both groups are also reduced by air pollution.

Overall, we find that self-employed workers are less impacted by extreme temperatures and air pollution than wage workers. Without additional data on the mechanisms through which extreme temperatures and air pollution affect working time—such as information on the number of daily working hours or the number of days off work—we cannot determine the reasons for the differences in their effects on self-employed versus wage-earning workers. A possible explanation is that self-employed workers have greater flexibility in adjusting their working hours compared to wage-earning workers. They are also more likely to work alone or in smaller groups than wage-earning workers, and as a result, have greater autonomy in adjusting their work schedules. As shown in Table 1, self-employed workers reported significantly fewer working hours than wage-earning workers in 2022 (36 hours versus 46 hours in the last seven days). Unlike wage-earning workers, who typically work full-time, self-employed individuals may compensate for reduced working hours on days affected by illness or days with extreme temperatures or high air pollution by working more on other days. In contrast, wage-earning workers, while able to reduce working hours on days with extreme temperatures or high air pollution, often cannot make up for lost time on other days. Several qualitative studies in other countries also suggest that self-employed workers are less affected by high temperatures than wage earners are. For example, Rother et al. (2019) find that self-employed workers in South Africa adjust their working hours to avoid peak heat by starting earlier in the day or taking longer breaks during the hottest periods. Similarly, Kramer et al. (2020), Schmidt (2022), and Habibi et al. (2024) report that self-employed workers adopt various adaptive strategies to cope with environmental stressors, such as redistributing workloads across different times of day (e.g., working in the early morning or evening) and changing work locations.

In Table 4, we conduct additional analysis to gain insight into differences in the impact of extreme temperatures and air pollution between self-employed and wage workers. Extreme temperatures are measured by the number of days with temperatures below the 5th percentile and above the 95th percentile. The estimated effects of cold and heat waves are similar and therefore not presented. In columns 1 and 2, we separate wageworkers into two groups: those with formal jobs and those with informal jobs. A formal job is defined as one that provides social insurance.

Table 4: 2SLS regression of log of working hours in the past 7 days for different groups of wageworkers

Explanatory variables	Informal wage workers	Formal wage workers	Workers paid fixed salary	Workers paid by days or hours	Workers paid by output or sales
	(1)	(2)	(3)	(4)	(5)
PM 2.5 (µg/m3)	-0.0113***	-0.0186***	-0.0136***	-0.0014	-0.0004
	(0.0021)	(0.0022)	(0.0028)	(0.0030)	(0.0031)
Number of days below the 5th temperature percentile	0.0128***	0.0139***	0.0186***	0.0192***	0.0167***
	(0.0014)	(0.0018)	(0.0020)	(0.0023)	(0.0021)
Number of days above the 95th temperature percentile	-0.0059***	-0.0068***	-0.0030***	-0.0034***	-0.0026***
	(0.0005)	(0.0009)	(0.0007)	(0.0007)	(0.0009)
Control variables	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes
Constant	5.5875***	-4.4984***	-7.8073***	4.8330**	3.6248*
	(1.5226)	(1.6888)	(2.3373)	(2.1313)	(2.1544)

Observations	723,439	807,364	376,955	240,861	120,639

Note: This table reports 2SLS regression of working hours on PM2.5, temperature variables, and other control variables. The instrumental variable for PM2.5 is wind direction dummies. Individual-level control variables include age, age squared, gender, education level dummies, and urban dummy of individuals. District-level control variables include monthly precipitation, wind speed, air pressure, thermal inversion, and humidity.

Columns 1 and 2 use data from the 2015–2022 LFSs, while Columns 3 to 5 use data from the 2015–2018 LFSs, as information on payment schemes is unavailable in LFSs from 2019 onward.

Robust standard errors in parentheses. The standard errors are clustered at the district level.

*** p<0.01, ** p<0.05, * p<0.1.

The table shows that air pollution and extreme temperatures tend to have lower negative effects on the working hours of informal workers than those of formal workers (columns 1 and 2). This is likely because informal workers have more flexible schedules.

A possible reason why formal workers are less affected by environmental changes is that they have access to paid leave and receive a fixed monthly salary, which is not impacted by reductions in working time. The LFSs conducted before 2019 include a question on the payment schemes of wageworkers. Based on this information, we classify workers into three groups: (i) those with a fixed monthly salary, (ii) those paid by the day or hour, and (iii) those paid by output or sales (piece-rate workers). In 2018, 46% of wageworkers received a fixed monthly salary, 36% were paid by the day or hour, and 18% were paid based on output or sales. Compared to informal workers, formal workers are more likely to receive a fixed salary: in 2018, 69% of formal workers were paid monthly, while only 21% of informal workers fell into this category.

Columns 3 to 5 in Table 4 present the effects of extreme temperatures and air pollution on working hours for workers with different payment schemes using LFS data from 2015 to 2018. The effects of temperature extremes on working hours are similar across workers with different payment schemes. However, the effect of air pollution is more pronounced among workers with fixed salaries. For workers paid by time or output, the impact of air pollution on working hours is small and statistically insignificant. This finding supports our argument that workers with fixed salaries are more responsive to air pollution, as their earnings are not directly affected by reduced working hours

4.2. Impacts on labor force participation and employment status

In Table 5, we analyze the effects of extreme temperatures and PM2.5 on labor force participation and employment status using 2SLS regressions. The sample include all individuals aged 15 and above, including those not in the labor force. Extreme temperatures and PM2.5 are measured over the past 12 months rather than the current month. The first-stage regressions are presented in Table A.8 in the Appendix, in which the average wind directions over the past 12 months are used as instrumental variables for the average PM2.5 concentration during the same period. The correlation between wind directions and PM2.5 remains strong, but it is not as strong as the correlation between monthly wind directions and monthly PM2.5 concentrations.

In Table 5, cold and heat waves are defined as periods of at least 3 consecutive cold or hot days, respectively. We also explore alternative definitions using durations of 5 and 7 consecutive days. The impacts of these longer cold and heat waves, reported in Appendix Table A.9, are consistent with the impacts of the three-day definitions presented in Table 4. We also present fixed-effects regression results in Appendix Tables A.10 and A.11 for comparison.

Table 5 indicates that high temperature bins as well as heat waves do not significantly affect labor force participation or employment status. Cold days have a positive and significant impact on the probability of being employed. While the coefficient for heat waves in the employment regression is also positive, it is not statistically significant at the 5% level. Notably, high temperature extremes reduce the probability of being self-employed while increasing the probability of holding a wage-earning job. This suggests that individuals may shift from self-employment to wage-earning jobs in response to high-temperature extremes.

Regarding air pollution, we do not find a significant effect of PM2.5 on labor force participation or employment. While individuals may reduce their working hours in response to high air pollution in the short term, they appear unable to adjust their long-term labor force participation in response to air pollution.

Table 5: 2SLS regression of employment variables on extreme temperatures and PM2.5 during the past 12 months

Explanatory variables	Dependent variables							
	Labor force participation (yes=1, no=0)	Having a work (yes=1, no=0)	Having a self-employed work (yes=1, no=0)	Having a wage-earning job (yes=1, no=0)	Labor force participation (yes=1, no=0)	Having a work (yes=1, no=0)	Having a self-employed work (yes=1, no=0)	Having a wage-earning job (yes=1, no=0)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PM 2.5 (μg/m3)	0.0034	0.0045	-0.0051	0.0018	0.0032	0.0042	-0.0041	0.0007
	(0.0057)	(0.0059)	(0.0072)	(0.0066)	(0.0057)	(0.0059)	(0.0072)	(0.0066)
Number of days below the 5th temperature percentile	0.0004*	0.0005**	-0.0003	0.0004				
	(0.0002)	(0.0002)	(0.0003)	(0.0003)				
Number of days above the 95th temperature percentile	0.0001	0.0002*	-0.0005***	0.0004***				
	(0.0001)	(0.0001)	(0.0001)	(0.0001)				
Number of days with at least 3 consecutive days below the 5th temperature percentile					0.0003	0.0004*	-0.0005*	0.0005*
					(0.0002)	(0.0002)	(0.0003)	(0.0003)
Number of days with at least 3 consecutive days above the 95th temperature percentile					0.0000	0.0001	-0.0005***	0.0003***
					(0.0001)	(0.0001)	(0.0001)	(0.0001)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.7497	-2.9244	48.2434***	-14.5033	-0.1115	-2.0733	44.9979***	-10.7243
	(13.1428)	(13.6189)	(16.5907)	(15.2577)	(13.1269)	(13.5983)	(16.5388)	(15.1007)
Observations	4,869,818	4,869,818	4,869,818	4,869,818	4,869,818	4,869,818	4,869,818	4,869,818

Note: This table reports 2SLS regression of employment on PM2.5, temperature variables, and other control variables. The instrumental variable for PM2.5 is wind direction dummies. Individual-level control variables include age, age squared, gender, education level dummies, and urban dummy of individuals. District-level control variables include monthly precipitation, wind speed, air pressure, thermal inversion, and humidity.
Robust standard errors in parentheses. The standard errors are clustered at the district level.
*** p<0.01, ** p<0.05, * p<0.1.

4.3. Robustness checks

We find significant effects of extreme temperatures and air pollution on working hours and earnings of employed people. We conduct several robustness analyses to assess the sensitivity of these estimates. To keep the presentation concise, we focus on the robustness checks for the effects of extreme temperatures and cold/heat waves defined as 3 consecutive cold or hot days. Robustness analyses for temperature bins and cold/heat waves defined using thresholds of 5 or 7 consecutive days are not presented.

Firstly, we examine whether the estimates are sensitive to the control variables. In Tables 2 and 3, we control for a number of individual-level and district-level variables. In Table A.12 and A.13 in the Appendix, we only control for age and gender of individuals. The estimated effects of air pollution are very similar to those in the previous tables. We also estimate models with additional control variables, specifically including province-by-month fixed effects, as shown in Tables A.13 and A.14 in the Appendix. These fixed effects account for province-specific seasonal patterns. The results are consistent with those in Tables 2 and 3, showing that high-temperature extremes and air pollution reduce working hours and earnings, while low-temperature extremes increase working hours. In this study, we use the ivreg2 command in Stata (Baum, Schaffer & Stillman, 2002) to estimate the 2SLS regressions, and the fixed effects are included as dummy variables. Incorporating province-by-month fixed effects significantly increases the computational burden and time required for estimation. Thus, we control province-by-month fixed effects for a robustness check. In theory, we can use even more control variables including district-by-year fixed effects, district-by-month fixed effects, and year-month fixed effects. However, this conservative approach results in a very large number of explanatory variables, making it impossible to estimate the model using the ivreg2 command in Stata.

Secondly, we restrict the sample to individuals aged 15–64, the primary working-age population. In the main text, we use a sample of individuals aged 15 and older. The effects of extreme temperatures and air pollution on individuals aged 15–64, presented in Appendix Tables A.16 and A.17, are very similar to those for individuals aged 15 and older.

Thirdly, we examine whether the impact estimates are sensitive to the use of sampling weights. As mentioned earlier, the LFSs are two-stage stratified surveys, and we apply sampling weights in the main analysis. In Tables A.18 and A.19, we estimate the effects of extreme temperatures and air pollution without using sampling weights. The results are consistent with those obtained when using sampling weights.

Fourthly, we test the sensitivity of the impact estimates to different methods of clustering standard errors. In Tables A.20 and A.21 in the Appendix, we cluster the standard errors at the enumeration-area level. We also use heteroscedasticity-robust standard errors in Tables A.22 and A.23 in the Appendix. The results are very similar to those obtained using standard errors clustered at the district level.

4.4. Heterogeneous effects

In Tables 2 and 3, we observe that the reducing effect of extreme temperatures and air pollution on the working hours of wage-earning workers tends to be larger than the effect on self-employed workers. This difference in effect magnitude may be attributed to differences in the characteristics of wage-earning and self-employed workers. In this section, we further examine the heterogeneous effects of extreme temperatures and air pollution across different groups of workers. For simplicity, we focus on their impact on working hours of workers. The results on the impact of monthly earning are reported in Table A.24, Figure A.6 and A.7 in the Appendix.

We first examine the heterogeneous impact of extreme temperatures and air pollution based on the level of outdoor exposure. While the health of outdoor workers is directly affected by these environmental factors, this does not necessarily imply that their working hours and earnings are more negatively impacted than those of other workers. In this study, we use the outdoor exposure classification from the Occupational Information Network (O*NET OnLine), sponsored by the U.S. Department of Labor, to measure workers' level of outdoor exposure. O*NET OnLine assigns an outdoor exposure score to 878 occupations in the U.S., ranging from 0 to 100, with higher scores indicating greater outdoor exposure.[5] The score reflects the frequency of outdoor work required in each occupation: 100 – Every day; 75 – Once a week or more, but not every day; 50 – Once a month or more, but not every week; 25 – Once a year or more, but not every month; and 0 – Never. We manually merged occupation codes from O*NET OnLine with the 3-digit ISCO (International Standard Classification of Occupations) codes used in the LFSs to measure workers' outdoor exposure. Based on the outdoor exposure scores, we classify workers into four groups: No outdoor exposure: score = 0; Low outdoor exposure: score between 0 and 50; Moderate outdoor

[5] For detailed information, see https://www.onetonline.org/find/descriptor/result/4.C.2.a.1.c

exposure: score between 50 and 90; High outdoor exposure: score between 90 and 100. In 2022, the shares of workers in these four groups were 13%, 44%, 19%, and 24%, respectively.

In addition, we use the classification from Causa et al. (2024) to define high-polluting and low-polluting occupations (classified using 3-digit ISCO codes). High-polluting occupations are identified according to emissions per worker across seven pollutants: carbon monoxide, nonmethane volatile organic compounds, nitrogen oxides, sulfur oxides, PM10, PM2.5, and carbon dioxide. In 2022, 73% of workers were in low-pollution occupations, while 27% were in high-polluting occupations.

Table 6 presents the estimated effects of extreme temperatures and air pollution on the working hours of individuals employed in occupations with varying degrees of outdoor exposure and pollution intensity. Corresponding estimates for monthly earnings are reported in Appendix Table A.24. The results indicate that the reducing effects of extreme temperatures and PM2.5 on working hours are smaller for workers in occupations with higher outdoor exposure and for those employed in high-polluting occupations. As discussed in a previous section, self-employed individuals have greater flexibility in adjusting their labor time in response to environmental conditions. In Figure A.8 in the Appendix, we estimate the proportion of wage workers for different population subgroups. It shows that workers in outdoor and high-pollution occupations have significantly lower rates of wage employment. They are more likely to be self-employed and, as a result, their working hours are less affected.

Table 6. 2SLS regression of log of working hours in the past 7 days by levels of outdoor and air pollution exposure

Explanatory variables	Occupations without outdoor exposure	Occupations with moderate outdoor exposure	Medium outdoor exposure occupation	Occupations with high outdoor exposure	Low air pollution exposure	High air pollution exposure
	(1)	(2)	(3)	(4)	(5)	(6)
PM 2.5 (μg/m3)	-0.0153***	-0.0154***	-0.0111***	-0.0074***	-0.0130***	-0.0077***
	(0.0048)	(0.0019)	(0.0022)	(0.0025)	(0.0020)	(0.0019)
Number of days below the 5th temperature percentile	0.0054**	0.0135***	0.0109***	0.0091***	0.0110***	0.0098***
	(0.0021)	(0.0015)	(0.0014)	(0.0011)	(0.0013)	(0.0009)
Number of days above the 95th temperature percentile	-0.0092***	-0.0060***	-0.0048***	-0.0012**	-0.0054***	-0.0027***
	(0.0014)	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0005)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.2934	0.2198	4.5023***	4.1261***	2.2723*	4.6074***
	(3.9753)	(1.3666)	(1.2630)	(1.6006)	(1.3232)	(1.3086)
Observations	267,642	1,446,200	630,244	1,239,738	2,225,402	1,358,422

Note: This table reports 2SLS regression of working hours on PM2.5, temperature variables, and other control variables. The instrumental variable for PM2.5 is wind direction dummies. Individual-level control variables include age, age squared, gender, education level dummies, and urban dummy of individuals. District-level control variables include monthly precipitation, wind speed, air pressure, thermal inversion, and humidity.

Robust standard errors in parentheses. The standard errors are clustered at the district level.

*** p<0.01, ** p<0.05, * p<0.1.

To further investigate this issue, we divide the sample into self-employed and wage workers and examine the heterogeneous effects of extreme temperatures and air pollution across occupations with varying degrees of outdoor exposure. Columns 1 to 4 of Table 7 show that among self-employed workers, the adverse effects of extreme temperatures and PM2.5 tend to be smaller for those in occupations with higher outdoor exposure. One plausible explanation is that these workers are predominantly engaged in the agricultural sector. In our sample, 92% of workers with high outdoor exposure are self-employed in agriculture. Self-employed agricultural workers typically have higher autonomy in adjusting their work schedules, allowing them to reduce labor supply during periods of extreme temperatures or high pollution and compensate by working more during less severe conditions.

In contrast, columns 5 to 8 of Table 7 show that wage workers are more sensitive to the level of outdoor exposure. Unlike the self-employed, wage workers have limited flexibility to modify their work schedules and are therefore more likely to reduce working hours in response to adverse environmental conditions. The negative effects of environmental factors—particularly PM2.5—on working hours are more pronounced among wage workers in high-exposure occupations.

Table 7. 2SLS regression of log of working hours in the past 7 days of self-employed and wage workers by levels of outdoor and air pollution exposure

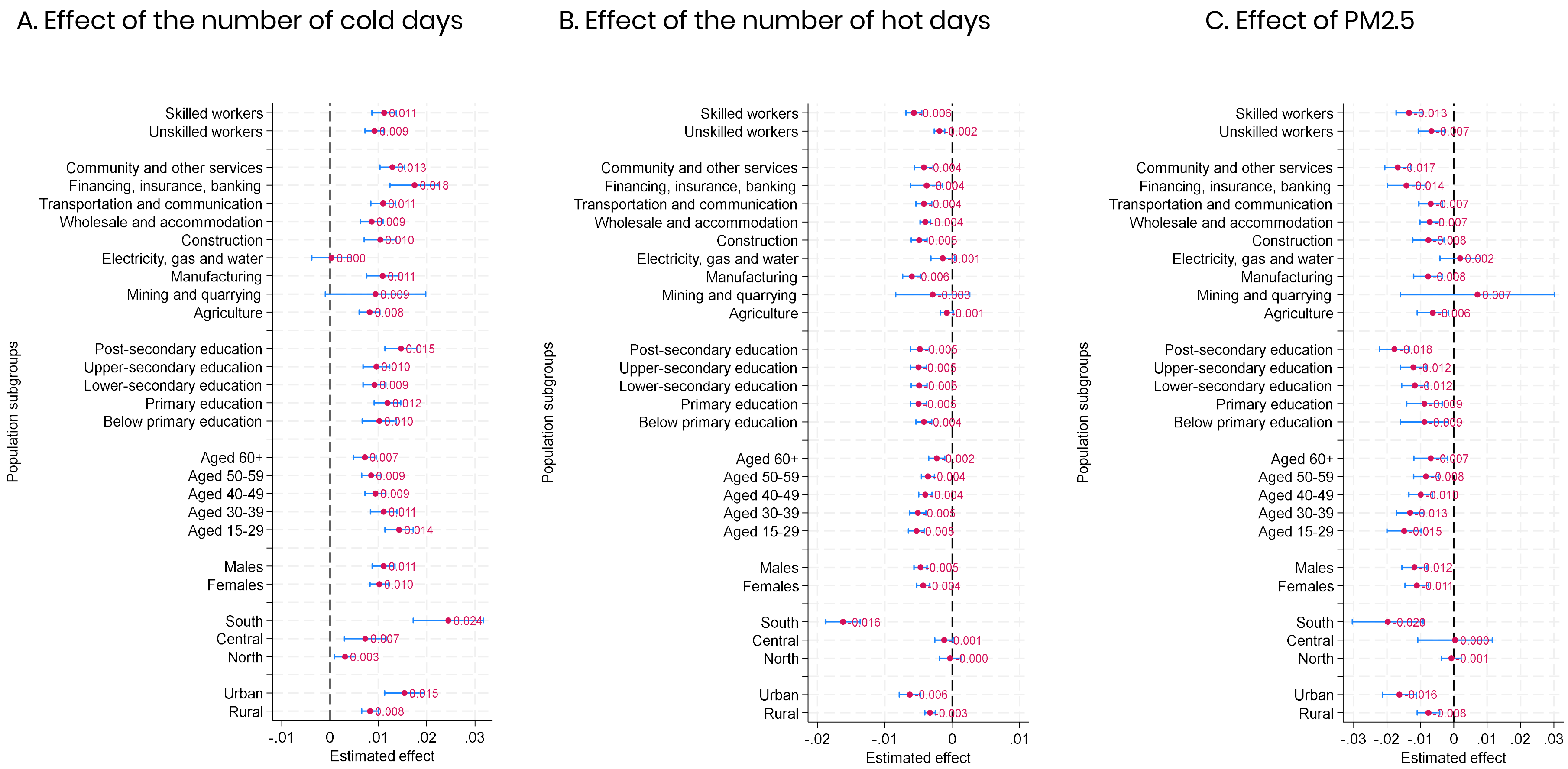
Explanatory variables	Self-employed workers				Wage workers			
	Occupations without outdoor exposure	Occupations with moderate outdoor exposure	Medium outdoor exposure occupation	Occupations with high outdoor exposure	Occupations without outdoor exposure	Occupations with moderate outdoor exposure	Medium outdoor exposure occupation	Occupations with high outdoor exposure
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PM 2.5 (µg/m3)	-0.0231*	-0.0127***	-0.0086***	-0.0058**	-0.0109***	-0.0177***	-0.0122***	-0.0250***
	(0.0126)	(0.0020)	(0.0025)	(0.0025)	(0.0018)	(0.0021)	(0.0025)	(0.0076)
Number of days below the 5th temperature percentile	0.0142***	0.0114***	0.0084***	0.0084***	0.0061***	0.0151***	0.0122***	0.0194***
	(0.0036)	(0.0014)	(0.0014)	(0.0011)	(0.0018)	(0.0017)	(0.0016)	(0.0035)
Number of days above the 95th temperature percentile	-0.0114***	-0.0051***	-0.0026***	-0.0007	-0.0052***	-0.0067***	-0.0063***	-0.0068***
	(0.0034)	(0.0005)	(0.0007)	(0.0005)	(0.0007)	(0.0008)	(0.0007)	(0.0011)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	4.5366	3.3742**	4.4073**	5.0795***	0.6442	-2.4985	5.3753***	3.4663
	(7.6045)	(1.4555)	(1.7934)	(1.6455)	(1.9204)	(1.7159)	(1.5356)	(3.5437)
Observations	87,555	623,458	230,862	1,111,146	180,087	822,742	399,382	128,592

Note: This table reports 2SLS regression of working hours on PM2.5, temperature variables, and other control variables. The instrumental variable for PM2.5 is wind direction dummies. Individual-level control variables include age, age squared, gender, education level dummies, and urban dummy of individuals. District-level control variables include monthly precipitation, wind speed, air pressure, thermal inversion, and humidity.
Robust standard errors in parentheses. The standard errors are clustered at the district level.
*** p<0.01, ** p<0.05, * p<0.1.

Similar, we estimate the effects of the number of cold and hot days and PM2.5 on working hours using the same model specification as in Table 2 for various population subgroups disaggregated by skill level, economic sectors, regions, urban/rural areas, regions, age, gender and education of workers. Regarding regions, we estimate the effects of extreme temperatures and PM2.5 separately for each of the six regions. However, the results indicate no statistically significant effects of PM2.5 across individual regions, and the estimated effects of extreme temperatures are also generally less significant. This lack of significance is likely due to the limited within-region variation in extreme temperatures and air pollution (see Figures 2 and 6). To estimation efficiency, we aggregate the six regions into three broader regional groups: (i) North (Northern Midlands and Mountain Areas and Red River Delta), (ii) Central (North Central and Central Coastal Areas and Central Highlands), and (iii) South (Southeast and Mekong River Delta). We present the effect estimates of extreme temperatures and PM2.5 for each of these three aggregated regions.

We present the effect estimates and their 95% confidence intervals for the number of days below the 5th temperature percentile and above the 95th temperature percentile and PM2.5 in Figure 8. Panel A of Figure 8 shows that low-temperature extremes increase working hours across most groups of workers. The effects are similar between skilled and unskilled workers, as well as across different economic sectors. Similarly, low-temperature extremes have comparable effects on individuals with varying education levels and between males and females. However, we find that the positive effect of low-temperature extremes is more pronounced for younger individuals compared to older ones. The effect is also greater in urban areas than in rural areas. By regions, the effect in the South is larger than that in the Central and Northern regions.

Figure 8: The effect of extreme temperatures and air pollution on log of working hours



Note: Panels A and B graph the estimates and their 95% confidence intervals of the effect of the number of days below the 5th percentile and the number of days above the 95th percentile of temperature distribution log of working hours of different population sub-groups. Panel C presents the estimates and their 95% confidence intervals of the effect of PM2.5 on log of working hours of different population sub-groups. The model specification is the same as Table 2.

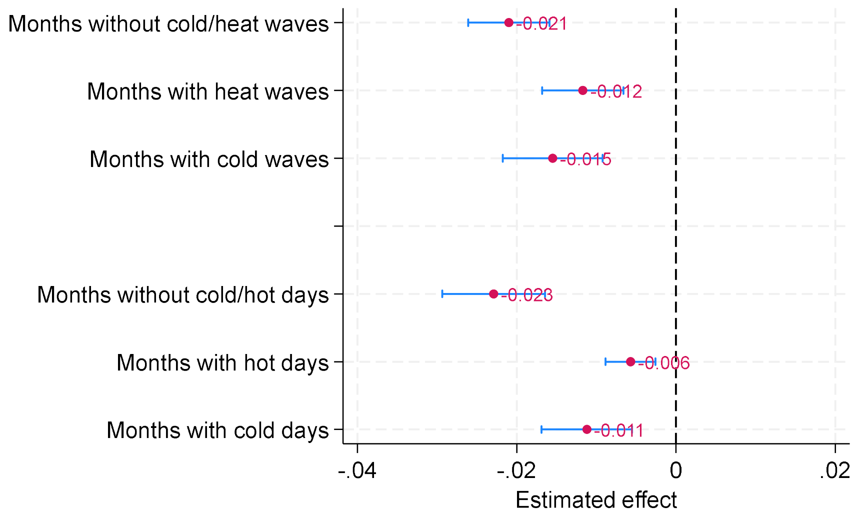
Panel B of Figure 8 shows a negative effect of high-temperature extremes on working hours across most worker groups. High-temperature extremes tend to have a greater (negative) impact on skilled workers compared to unskilled workers. An additional hot day reduces the working hours of skilled workers by 0.6% and unskilled workers by 0.2%. The negative effect of high-temperature extremes on working hours is more pronounced in urban areas and the Southern region than in rural areas and the Northern and Central regions. Additionally, high-temperature extremes tend to have a greater effect on younger workers than on older workers. It is worth noting that younger individuals are more likely to hold skilled jobs and reside in urban areas and the Southern region compared to older individuals.

Similar to extreme temperatures, PM2.5 concentrations have a greater (negative) impact on the working hours of skilled and younger workers, as well as those residing in urban areas and the Southern region, compared to unskilled and older workers and those living in rural areas and the Northern and Central regions, respectively (Panel C). Higher-education workers are more likely to reduce working hours than lower-education ones. Regarding economic sectors, we expected workers in open-air industries, such as agriculture and transportation, to be more responsive to extreme temperatures and air pollution. However, our analysis does not provide evidence to support this hypothesis.

As discussed in a previous section, compared to self-employed workers, wage-earning workers have less flexibility in adjusting their working time, and their working hours are more susceptible to the effects of extreme temperatures and air pollution. Figure A.8 in the Appendix shows that urban areas and the Southern region also have a higher share of wageworkers than rural areas and other regions. By demographic characteristics, younger, highly educated, and skilled workers are more likely to be wage-earning workers. Consequently, their working hours are more affected by extreme temperatures and air pollution than those of older, less educated, unskilled, and rural workers, who are more likely to be self-employed. Similarly, the difference in the effect of extreme temperatures and air pollution across regions and economic sectors is also partly explained by the difference in the share of wage-workers across regions and economic sectors.

Finally, we examine the interaction effects of extreme temperatures and air pollution on working hours and earnings. In Figure 9, we estimate the impact of PM2.5 concentrations on the logarithm of working hours and monthly earnings during months with and without extreme temperatures. The sample is divided based on whether individuals were interviewed in months containing extreme temperatures or not. The results show that the effects of PM2.5 concentrations are stronger in months without extreme temperatures (i.e., months with temperatures consistently within the 5th–95th percentiles of the temperature distribution) compared to months with extreme temperatures. Similarly, the impact of PM2.5 concentrations is also greater in months without cold or heat waves than in months with such events. It is important to note that the interaction effect differs from the combined or total effect of extreme temperatures and air pollution. Possibly, high-temperature extremes can already reduce working hours and earnings, and leaving less room for additional reductions caused by air pollution.

Figure 9: The effect of PM2.5 on log of working hours during months with and months without temperatures extremes



Note: This figure graphs the estimates and their 95% confidence intervals of the effect of PM2.5 on log of working hours and log of monthly earnings during months with and months without temperatures extremes. The model specification is the same as Table 3.

5. Conclusions

Vietnam is one of the most exposed countries to climate change, with an expected increase in heat waves in the coming years. Additionally, Vietnam experiences higher-than-average air pollution levels, with PM2.5 concentrations exceeding the global average. Using data from the LFSs 2015-2022, this study examines the impact of extreme temperatures and air pollution on labor supply and earnings in Vietnam.

While extreme temperatures and air pollution do not significantly influence labor force participation, they do affect workers' working hours. People tend to work more during months with low-temperature extremes and less during months with high-temperature extremes. Reduced working hours due to high temperatures also result in lower earnings for workers. Regarding air pollution, we find that higher PM2.5 concentrations reduce both working hours and earnings. The negative effect of PM2.5 is larger than the effect of high temperature extremes. Notably, the negative effect of PM2.5 is larger in magnitude than that of high-temperature extremes.

The effects of extreme temperatures and air pollution are more pronounced among younger, skilled, urban, and outdoor workers, compared to older, unskilled, rural, and indoor workers. A possible explanation is that these workers are more likely to be employed in wage jobs. Unlike the self-employed, wage workers have less flexibility in adjusting their work schedules in response to environmental shocks, making their total working hours more sensitive to such conditions. The impact of air pollution and extreme temperatures on monthly wages tends to be larger for workers covered by social insurance than for informal workers, but in both instances the results raise the question of how preventive measures, such as heat adaptation plans or pollution control regulations, could better support wage fluctuations for workers during extreme weather or pollution events. Additionally, we find that the impact of PM2.5 concentrations is greater in months without extreme temperatures than in months with such events. This may be because extreme temperatures already reduce working hours and earnings, leaving less scope for further reductions caused by air pollution. To understand this result, we explore outdoor work. Despite greater exposure, outdoor workers show smaller reductions in hours than indoor workers do, likely because many are self-employed and have more flexibility to adjust their schedules in response to climatic shocks. However, when focusing only on wage earners, those with high outdoor exposure face larger negative effects of extreme temperatures and air pollution. Overall, our results confirm that working hours and earnings respond more strongly to air pollution than to extreme temperatures.

This study offers several important policy implications. First, government measures should account for workers' schedule sensitivity to air quality to mitigate the adverse effects of extreme temperature and air pollution events, for example by expanding Occupational Safety and Health regulations, especially related to air pollution. Although the government has established regulations concerning acceptable temperature ranges in workplaces, set between 16 and 34°C (MOH, 2016), there are currently no standards regulating air pollution levels in workplaces. Vietnam could engage in the definition of pioneering Indoor Air Quality Standards, like the United Arab Emirates indoor air quality regime, or through the definition of "occupational air quality limits", similar to the Environmental Management and Co-ordination (Air Quality) Regulations of Kenya (UNEP, 2021). Second, the government should implement policies and measures to improve responsiveness to air quality deterioration and more frequent extreme temperatures, like heat waves, by supporting the healthcare system and environmental infrastructures. Strengthening the healthcare system can for instance ensure better access to medical services for workers whose health is affected by air pollution and extreme temperatures. Additionally, supporting the accessibility and installment of air purifiers and air conditioners in workplaces and homes could help mitigate the adverse effects of these environmental events. Measures to filter pollutants and regulate temperature could be particularly useful in urban work environments as well as in public transports. Third, given that extreme temperatures and air pollution impact various groups of workers to differing degrees, support measures should be customized to meet the specific needs of each group. For example, the government could partner with the private sector to pilot schemes offering flexible hours or remote work options in wage employment contracts, to test their effectiveness during extreme temperatures' periods to maintain labor productivity and quality across different skilled occupations, or for young workers joining a workplace. In addition, to address informal workers wage reduction during high-pollution days, municipalities could test air-quality information systems (like app-based or messaging alerts) that, beyond communicating on health risks and safety guidance, provide advice on how to adjust work hours and reduce exposure in different types of work environments. Furthermore, tailored urban planning strategies could play a role to support workers livelihoods, with actions like greening the areas where informal trading markets operate.

Bibliography

Bonelli, S., Charbit, S., Kageyama, M., Woillez, M. N., Ramstein, G., Dumas, C., & Quiquet, A. (2009). Investigating the evolution of major Northern Hemisphere ice sheets during the last glacial-interglacial cycle. *Climate of the Past*, 5(3), 329-345.

Yilmaz, S. D., & Godin, A. (2024). Strongly Sustainable Development Trajectories: The Road to Social, Environmental, and Macroeconomic Stability–Introduction. International *Journal of Political Economy*, 53(1), 1-3.

Ab Manan, N., Aizuddin, A. N., & Hod, R. (2018). Effect of air pollution and hospital admission: a systematic review. *Annals of Global Health*, 84(4), 670.

Adhvaryu, A., Kala, N., & Nyshadham, A. (2020). The light and the heat: Productivity co-benefits of energy-saving technology. *Review of Economics and Statistics*, 102(4), 779-792.

Anderson, B. G., & Bell, M. L. (2009). Weather-related mortality: How heat, cold, and heat waves affect mortality in the United States. *Epidemiology*, 20(2), 205–213.

Arceo, E., Hanna, R., Oliva, P., (2016). Does the effect of pollution on infant mortality differ between developing and developed countries? Evidence from Mexico city. *Economic Journal*, 126 (591), 257–280.

AUSTIN, W., CARATTINI, S., GOMEZ-MAHECHA, J., & PESKO, M. F. (2023). The effects of contemporaneous air pollution on COVID-19 morbidity and mortality. *Journal of Environmental Economics and Management*, 119, 102815.

Baum, C.F., Schaffer, M. E. & Stillman, S. (2002). "IVREG2: Stata module for extended instrumental variables/2SLS and GMM estimation," Statistical Software Components S425401, Boston College Department of Economics, revised 14 Aug 2024.

Baum-Snow, N., and Lutz, B. F. (2011). School Desegregation, School Choice, and Changes in Residential Location Patterns by Race. *American Economic Review* 101(7): 3019–3046.

Block, S., Emerson, J. W., Esty, D. C., de Sherbinin, A., Wendling, Z. A., et al. (2024). Environmental Performance Index. New Haven, CT: Yale Center for Environmental Law & Policy. Available at: https://epi.yale.edu/measure/2024/AIR

Caserini, S., Giani, P., Cacciamani, C., Ozgen, S., & Lonati, G. (2017). Influence of climate change on the frequency of daytime temperature inversions and stagnation events in the Po Valley: historical trend and future projections. *Atmospheric Research*, 184, 15-23.

Causa, O., Nguyen, M., & Soldani, E. (2024). A new measurement approach for identifying high-polluting jobs across European countries. *OECD Economics Department Working Papers* No. 1795. https://dx.doi.org/10.1787/f5127e4c-en

Chang, T. Y., Graff Zivin, J., Gross, T., & Neidell, M. (2019). The effect of pollution on worker productivity: evidence from call center workers in China. *American Economic Journal: Applied Economics*, 11(1), 151-172.

Chen, S., Oliva & P., Zhang, P. (2022). The effect of air pollution on migration: evidence from China. *Journal of Development Economics*, 156, 102833.

Dell, M., Jones, B., & Olken, B. (2012). Temperature extremes and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, 4(3), 66-95.

Deryugina, T., & Hsiang, S. (2017). The marginal product of climate (No. w24072). National Bureau of Economic Research.

Deryugina, T., & Hsiang, S. M. (2014). Does the environment still matter? Daily temperature and income in the United States (No. w20750). National Bureau of Economic Research.

Deryugina, T., Heutel, G., Miller, N. H., Molitor, D., & Reif, J. (2019). The mortality and medical costs of air pollution: Evidence from changes in wind direction. *American Economic Review*, 109(12), 4178-4219.

Deschênes, O., & Greenstone, M. (2011). Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US. *American Economic Journal: Applied Economics*, 3(4), 152-185.

Deschenes, O., Wang, H., Wang, S., Zhang, P., (2020). The effect of air pollution on body weight and obesity: Evidence from China. *J. Dev. Econ.* 145, 102461.

Dimitrova, A., Ingole, V., Basagaña, X., Ranzani, O., Mila, C., Ballester, J., & Tonne, C. (2021). Association between ambient temperature and heat waves with mortality in South Asia: Systematic review and meta-analysis. *Environment International*, 146, 106170.

Dominski, F. H., Branco, J. H. L., Buonanno, G., Stabile, L., da Silva, M. G., & Andrade, A. (2021). Effects of air pollution on health: A mapping review of systematic reviews and meta-analyses. *Environmental Research*, 201, 111487.

Ebi, K. L., Vanos, J., Baldwin, J. W., Bell, J. E., Hondula, D. M., Errett, N. A., Hayes, K., Reid, C., Saha, S., Spector, J. & Berry, P. (2021). Extreme weather and climate change: population health and health system implications. *Annual Review of Public Health*, 42(1), 293-315.

Goodenberger, J., Munk, R., & Senney, G. (2024). The interactive effects of temperature and air quality on productivity. *Applied Economics*, 1-18.

GSO (2024), Danh mục hành chính Việt Nam 2022 (in English: The list of administrative units in Vietnam 2022). General Statistics Office of Vietnam. Accessed on September 15, 2024. Available at: https://danhmuchanhchinh.gso.gov.vn

Habibi, P., Razmjouei, J., Moradi, A., Mahdavi, F., Fallah-Aliabadi, S., & Heydari, A. (2024). Climate change and heat stress resilient outdoor workers: findings from systematic literature review. BMC Public Health, 24(1), 1711.

Han, A., Kim, T., Ten, G. K., & Wang, S. (2023). Air pollution and gender imbalance in labor supply responses: Evidence from South Korea. *Economic Modelling*, 124, 106290.

He, J., Liu, H., & Salvo, A. (2019). Severe air pollution and labor productivity: Evidence from industrial towns in China. *American Economic Journal: Applied Economics*, 11(1), 173-201.

He, J., Liu, H., & Salvo, A. (2019). Severe air pollution and labor productivity: Evidence from industrial towns in China. *American Economic Journal: Applied Economics*, 11(1), 173-201.

He, J., Liu, H., & Salvo, A. (2019). Severe air pollution and labor productivity: Evidence from industrial towns in China. American Economic Journal: *Applied Economics*, 11(1), 173-201.

Heckman, J., Lalonde, R., & Smith, J. (1999). The economics and econometrics of active labor market programs. In A. Ashenfelter & D. Card (Eds.), 1865–2097, Handbook of Labor Economics (Vol. 3). Elsevier Science.

Isphording, I. E., & Pestel, N. (2021). Pandemic meets pollution: poor air quality increases deaths by COVID-19. *Journal of Environmental Economics and Management*, 108, 102448.

Jhun, I., Coull, B. A., Schwartz, J., Hubbell, B., & Koutrakis, P. (2015). The impact of weather changes on air quality and health in the United States in 1994–2012. *Environmental Research Letters,* 10(8), 084009.

Kalisa, E., Fadlallah, S., Amani, M., Nahayo, L., & Habiyaremye, G. (2018). Temperature and air pollution relationship during heatwaves in Birmingham, UK. *Sustainable Cities and Society*, 43, 111-120.

Kent, S. T., McClure, L. A., Zaitchik, B. F., Smith, T. T., & Gohlke, J. M. (2014). Heat waves and health outcomes in Alabama (USA): The importance of heat wave definition. *Environmental Health Perspectives*, 122(2), 151–158.

Khajavi, A., Khalili, D., Azizi, F., & Hadaegh, F. (2019). Impact of temperature and air pollution on cardiovascular disease and death in Iran: a 15-year follow-up of Tehran Lipid and Glucose Study. Science of the Total Environment, 661, 243-250.

Khalesi, B., & Mansouri Daneshvar, M. R. (2020). Comprehensive temporal analysis of temperature inversions across urban atmospheric boundary layer of Tehran within 2014–2018. *Modeling Earth Systems and Environment*, 6(2), 967-982.

Kinney, P. L. (2018). Interactions of climate change, air pollution, and human health. Current *Environmental Health Reports*, 5, 179-186.

Kramer, C., & Wagner, M. (2020). Enhancing urban sustainable indicators in a German City—towards human-centered measurements for sustainable urban planning. World, 1(2), 104-123.

Li, J., & Meng, G. (2023). Pollution exposure and social conflicts: Evidence from China's daily data. *Journal of Environmental Economics and Management*, 121, 102870.

Li, Y., & Chao, J. (2018). Theoretical urban heat island circulation in the temperature inversion profile. *Atmosphere*, 9(3), 98.

Meehl, G. A., & Tebaldi, C. (2004). More intense, more frequent, and longer lasting heat waves in the 21st century. *Science*, 305(5686), 994–997.

MOH (2016). Circular No. 26/2016/TT-BYT on Providing National Technical Regulations on Microclimate – Permissible Microclimate Values in the Workplace, Issued on 30/06/2016, Ministry of Health (MOH), Vietnam. Available at : https://thuvienphapluat.vn/ban-an/tin-tuc/quy-chuan-ve-dieu-kien-vi-khi-hau-tai-noi-lam-viec-quy-dinh-the-nao-8420

Neidell, M. P. (2023). Air pollution and worker productivity. IZA World of Labor. IZA, doi: 10.15185/izawol.363.v2

Ngo, T. X., Pham, H. V., Phan, H. D., Nguyen, A. T., To, H. T., & Nguyen, T. T. (2023). A daily and complete PM2. 5 dataset derived from space observations for Vietnam from 2012 to 2020. *Science of The Total Environment*, 857, 159537.

Nguyen, C. V., Nguyen, M. H., & Nguyen, T. T. (2023). The impact of cold waves and heat waves on mortality: Evidence from a lower middle-income country. *Health Economics*, 32(6), 1220-1243.

Nguyen, T., Ngo, T., Pham, A., Nguyen, L. & Ngo-Duc, T. (2025) Impact of Meteorological Factors and Extreme Weather Events on PM2:5 Pollution in Vietnam, AFD Research Papers no. 364

Olea, J. L. M., & Pflueger, C. (2013). A robust test for weak instruments. *Journal of Business & Economic Statistics*, 31(3), 358–369.

Orru, H., Ebi, K. L., & Forsberg, B. (2017). The interplay of climate change and air pollution on health. Current environmental health reports, 4, 504-513.

Pant, P., Huynh, W., & Peltier, R. E. (2018). Exposure to air pollutants in Vietnam: Assessing potential risk for tourists. *Journal of Environmental Sciences*, 73, 147-154.

Perkins, S. E. (2015). A review on the scientific understanding of heatwaves—Their measurement, driving mechanisms, and changes at the global scale. *Atmospheric Research*, 164, 242–267.

Perkins, S. E., & Alexander, L. V. (2013). On the measurement of heat waves. *Journal of Climate*, 26(13), 4500–4517.

Rangel, M. A., & Vogl, T. S. (2019). Agricultural fires and health at birth. *Review of Economics and Statistics*, 101(4), 616-630.

Rendón, A. M., Salazar, J. F., Palacio, C. A., Wirth, V., & Brötz, B. (2014). Effects of urbanization on the temperature inversion breakup in a mountain valley with implications for air quality. *Journal of applied meteorology and climatology*, 53(4), 840-858.

Rocque, R. J., Beaudoin, C., Ndjaboue, R., Cameron, L., Poirier-Bergeron, L., Poulin-Rheault, R. A., Fallon, C., Tricco, A., and Witteman, H. O. (2021). Health effects of climate change: an overview of systematic reviews. *BMJ Open*, 11(6), e046333.

Roth, J., Sant'Anna, P. H., Bilinski, A., & Poe, J. (2023). What's trending in difference-in-differences? A synthesis of the recent econometrics literature. *Journal of Econometrics*.

Rother, H. A., John, J., Wright, C. Y., Irlam, J., Oosthuizen, R., & Garland, R. M. (2019). Perceptions of occupational heat, sun exposure, and health risk prevention: a qualitative study of forestry workers in South Africa. Atmosphere, 11(1), 37.

Santamouris, M., Synnefa, A., & Karlessi, T. (2011). Using advanced cool materials in the urban built environment to mitigate heat islands and improve thermal comfort conditions. *Solar Energy*, 85(12), 3085-3102.

Schultz, A. B., Chen, C. Y., & Edington, D. W. (2009). The cost and impact of health conditions on presenteeism to employers: a review of the literature. Pharmacoeconomics, 27, 365-378.

Shah, A. S., Langrish, J. P., Nair, H., McAllister, D. A., Hunter, A. L., Donaldson, K., ... & Mills, N. L. (2013). Global association of air pollution and heart failure: a systematic review and meta-analysis. *The Lancet*, 382(9897), 1039-1048.

Sillmann, J., Aunan, K., Emberson, L., Büker, P., Van Oort, B., O'Neill, C., ... & Brisebois, A. (2021). Combined impacts of climate and air pollution on human health and agricultural productivity. *Environmental Research Letters*, 16(9), 093004.

Schmidt, C. W. (2022). Hot Pursuit: New Efforts to Prevent Heat-Related Illness on the Job. *Environmental Health Perspectives*, 130(9), 092001.

Somanathan, E., Somanathan, R., Sudarshan, A., & Tewari, M. (2021). The impact of temperature on productivity and labor supply: Evidence from Indian manufacturing. *Journal of Political Economy*, 129(6), 1797–1827.

Staiger, D., & Stock, J. H. (1997). Instrumental variables regression with weak instruments. *Econometrica*, 65(3), 557–586.

Tochihara, Y., Wakabayashi, H., Lee, J. Y., Wijayanto, T., Hashiguchi, N., & Saat, M. (2022). How humans adapt to hot climates learned from the recent research on tropical indigenes. *Journal of*

Physiological Anthropology, 41(1), 27.

Tran-Anh, Q., Ngo-Duc, T., Espagne, E., & Trinh-Tuan, L. (2023). A 10-km cmip6 downscaled dataset of temperature and precipitation for historical and future Vietnam climate. *Scientific Data*, 10 (1), 257.

Tuholske, C., Caylor, K., Funk, C., Verdin, A., Sweeney, S., Grace, K., Peterson, P., & Evans, T. (2021). Global urban population exposure to extreme heat. *Proceedings of the National Academy of Sciences*, 118(41), e2024792118.

UNEP (2021). Regulating Air Quality: The first global assessment of air pollution legislation, United Nations Environment Programme: Nairobi. ISBN: 978-92-807-3872-8.

West, J.J., C.G. Nolte, M.L. Bell, A.M. Fiore, P.G. Georgopoulos, J.J. Hess, L.J. Mickley, S.M. O'Neill, J.R. Pierce, R.W. Pinder, S. Pusede, D.T. Shindell, & S.M. Wilson, (2023) Ch. 14. Air quality. In: Fifth National Climate Assessment. Crimmins, A.R., C.W. Avery, D.R. Easterling, K.E. Kunkel, B.C. Stewart, and T.K. Maycock, Eds. U.S. Global Change Research Program, Washington, DC, USA. https://doi.org/10.7930/NCA5.2023.CH14

WHO (1990). Environmental health in rural and urban development and housing unit. Indoor Environment: Health Aspects of Air Quality, Thermal Environment, Light and Noise, 17

Wolfers, J. (2006). Did Unilateral Divorce Laws Raise Divorce Rates? A Reconciliation and New Results. *American Economic Review* 96(5): 1802–1820.

World Bank and Asian Development Bank (2021). Climate Risk Country Profile: Vietnam. Washington, DC: World Bank, and Manila: Asian Development Bank.

Zander, K. K., Botzen, W. J., Oppermann, E., Kjellstrom, T., & Garnett, S. T. (2015). Heat stress causes substantial labour productivity loss in Australia. *Nature Climate Change*, 5(7), 647-651.

Zhang, H., Wang, Y., Park, T. W., & Deng, Y. (2017). Quantifying the relationship between extreme air pollution events and extreme weather events. *Atmospheric Research*, 188, 64-79.

Zhao, M., Lee, J. K. W., Kjellstrom, T., & Cai, W. (2021). Assessment of the economic impact of heat-related labor productivity loss: a systematic review. *Climatic Change*, 167(1),

Zivin, J. G., & Neidell, M. (2012). The impact of pollution on worker productivity. *American Economic Review*, 102(7), 3652-3673.

Appendix

Table A.1. Characteristics of individuals in the sample

Variables	Year 2015	Year 2016	Year 2017	Year 2018	Year 2019	Year 2020	Year 2021	Year 2022
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age	40.3	40.8	40.5	40.8	40.3	40.6	41.2	42.0
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
Proportion of males (%)	51.4	51.4	51.7	52.2	52.7	52.9	53.4	52.0
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
Proportion of urban people (%)	31.5	32.2	32.0	32.3	32.2	32.7	36.2	35.0
	(1.7)	(1.7)	(1.5)	(1.5)	(1.8)	(1.9)	(2.0)	(1.9)
Proportion of individuals with less than	14.0	13.1	13.9	13.6	15.1	11.6	10.0	9.9
primary education (%)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)
Proportion of individuals with primary	23.3	23.0	22.7	22.2	21.4	21.5	21.1	21.2
education (%)	(0.4)	(0.4)	(0.3)	(0.3)	(0.4)	(0.4)	(0.5)	(0.4)
Proportion of individuals with lower-	31.4	31.6	31.1	31.3	29.5	30.9	31.6	32.0
secondary education (%)	(0.4)	(0.4)	(0.4)	(0.4)	(0.4)	(0.4)	(0.5)	(0.5)
Proportion of individuals with upper-	19.7	20.1	20.1	20.2	19.8	21.4	22.3	22.5
secondary education (%)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.4)	(0.4)	(0.5)
Proportion of individuals with post-	11.5	12.2	12.2	12.7	14.3	14.7	15.0	14.4
secondary education (%)	(0.4)	(0.5)	(0.4)	(0.4)	(0.5)	(0.5)	(0.6)	(0.6)

Note: The sample includes employed individuals who are aged 15 years old or more.
The standard errors of the means in parentheses.
Source: Estimation using data from the LFSs 2015-2022.

Table A.2. First-stage regression of monthly PM2.5

Explanatory variables	Dependent variable is PM 2.5 (µg/m3)				
	(1)	(2)	(3)	(4)	(5)
Wind direct degree [0, 45)	0.2967	1.4126***	1.5574***	1.8845***	1.9062***
	(0.2405)	(0.2391)	(0.2411)	(0.2568)	(0.2561)
Wind direct degree [45, 90)	0.5005**	1.4972***	1.6350***	1.9854***	1.9955***
	(0.2002)	(0.1966)	(0.1969)	(0.2096)	(0.2112)
Wind direct degree [90, 135)	0.9086***	2.2644***	2.3783***	2.6589***	2.7230***
	(0.1998)	(0.1990)	(0.2004)	(0.2153)	(0.2192)
Wind direct degree [135, 180)	2.4654***	3.7585***	3.8589***	4.0401***	4.0638***
	(0.1974)	(0.2276)	(0.2281)	(0.2402)	(0.2410)
Wind direct degree [180, 225)	1.7462***	3.5477***	3.6434***	3.7403***	3.7343***
	(0.1736)	(0.2148)	(0.2147)	(0.2236)	(0.2242)
Wind direct degree [225, 270)	0.5989***	1.8910***	1.9083***	1.9542***	1.9284***
	(0.1571)	(0.1718)	(0.1692)	(0.1792)	(0.1796)
Wind direct degree [270, 315)	0.6654***	1.1848***	1.1507***	1.1610***	1.1493***
	(0.1427)	(0.1465)	(0.1438)	(0.1503)	(0.1507)
Number of days 0–15°C	0.2256***				
	(0.0112)				
Number of days 15–18°C	0.2754***				
	(0.0142)				
Number of days 18–21°C	0.0602***				
	(0.0078)				
Number of days 24–27°C	-0.1478***				
	(0.0073)				
Number of days 27–30°C	-0.3064***				
	(0.0089)				
Number of days 30°C +	-0.5243***				
	(0.0154)				
No. of days below the 5th temperature percentile		0.3785***			
		(0.0169)			
No. of days above the 95th temperature percentile		-0.1003***			
		(0.0058)			
No. of days with at least 3 consecutive days below the 5th temperature percentile			0.3752***		
			(0.0163)		
No. of days with at least 3 consecutive days above the 95th temperature percentile			-0.0757***		
			(0.0057)		
No. of days with at least 5 consecutive days below the 5th temperature percentile				0.2228***	
				(0.0226)	
No. of days with at least 5 consecutive days above the 95th temperature percentile				-0.0642***	
				(0.0052)	
No. of days with at least 7 consecutive days below the 5th temperature percentile					0.2759***
					(0.0191)
No. of days with at least 7 consecutive days above the 95th temperature percentile					-0.0630***
					(0.0051)
Control variables	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes
Constant	191.577***	-663.395***	-684.883***	-705.436***	-715.474***
	(18.6360)	(28.7341)	(29.1325)	(29.747)	(29.392)
Observations	3,583,824	3,583,824	3,583,824	3,583,824	3,583,824
R-squared	0.872	0.864	0.862	0.859	0.859
Cragg Donald Wald *F* statistic	1.3e+04	2.2e+04	2.3e+04	2.3e+04	2.3e+04
Effective *F* statistic	66.67	87.48	90.67	91.48	94.09

Note: This table reports regression of PM2.5 on wind direction dummies, temperature variables, and other control variables. Individual-level control variables include age, age squared, gender, education level dummies, and urban dummy of individuals. District-level control variables include monthly precipitation, wind speed, air pressure, thermal inversion, and humidity.
Robust standard errors in parentheses. The standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.3. Fixed-effect and 2SLS regressions of employment variables on extreme temperatures and PM2.5

Explanatory variables	Fixed-effect regression		2SLS regressions	
	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings
	(1)	(2)	(3)	(4)
PM 2.5 (μg/m3)	0.0056***	0.0042***	-0.0085***	-0.0160***
	(0.0005)	(0.0012)	(0.0021)	(0.0057)
Number of days 0–15°C	-0.0023***	-0.0061***	0.0010	-0.0012
	(0.0006)	(0.0020)	(0.0007)	(0.0021)
Number of days 15–18°C	-0.0026***	-0.0072***	0.0014*	-0.0015
	(0.0006)	(0.0019)	(0.0007)	(0.0024)
Number of days 18–21°C	0.0001	-0.0022	0.0010**	-0.0009
	(0.0004)	(0.0014)	(0.0004)	(0.0014)
Number of days 21–24°C	0	0	0	0
Number of days 24–27°C	-0.0018***	0.0000	-0.0038***	-0.0028**
	(0.0003)	(0.0010)	(0.0005)	(0.0013)
Number of days 27–30°C	0.0016***	0.0066***	-0.0029***	0.0002
	(0.0005)	(0.0015)	(0.0007)	(0.0022)
Number of days 30°C +	-0.0017***	0.0013	-0.0094***	-0.0098***
	(0.0006)	(0.0020)	(0.0012)	(0.0036)
Control variables	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Constant	12.9195***	-6.4849**	15.6970***	-2.4228
	(1.0456)	(3.0084)	(1.1670)	(3.1339)
Observations	3,583,824	3,583,824	3,583,824	3,583,824
R-squared	0.096	0.184		

Note: This table reports fixed-effect and 2SLS regressions of employment on PM2.5, temperature bins, and other control variables. Individual-level control variables include age, age squared, gender, education level dummies, and urban dummy of individuals. District-level control variables include monthly precipitation, wind speed, air pressure, thermal inversion, and humidity.
Robust standard errors in parentheses. The standard errors are clustered at the district level.
*** p<0.01, ** p<0.05, * p<0.1.

Table A.4. Fixed-effect regression of employment variables on extreme temperatures and PM2.5

Explanatory variables	All workers		Self-employed workers		Wage-earning workers	
	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings
	(1)	(2)	(3)	(4)	(5)	(6)
PM 2.5 (µg/m3)	0.0042***	0.0021**	0.0039***	0.0041***	0.0044***	0.0023***
	(0.0004)	(0.0009)	(0.0005)	(0.0013)	(0.0004)	(0.0006)
Number of days below the 5th percentile of temperature distribution	0.0048***	-0.0055***	0.0044***	-0.0056***	0.0053***	-0.0038***
	(0.0006)	(0.0014)	(0.0006)	(0.0020)	(0.0008)	(0.0007)
Number of days above the 95th percentile of temperature distribution	-0.0026***	-0.0048***	-0.0015***	-0.0065***	-0.0040***	-0.0043***
	(0.0004)	(0.0009)	(0.0003)	(0.0013)	(0.0006)	(0.0007)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	14.3695***	6.9329***	14.1211***	9.0187***	15.2244***	10.1691***
	(0.7802)	(1.5943)	(0.8269)	(2.2565)	(0.9301)	(1.1967)
Observations	3,583,824	3,583,824	2,053,021	2,053,021	1,530,803	1,530,803
R-squared	0.095	0.184	0.134	0.195	0.067	0.134

Note: This table reports fixed-effect regression of employment on PM2.5, temperature variables, and other control variables. Individual-level control variables include age, age squared, gender, education level dummies, and urban dummy of individuals. District-level control variables include monthly precipitation, wind speed, air pressure, thermal inversion, and humidity.
Robust standard errors in parentheses. The standard errors are clustered at the district level.
*** p<0.01, ** p<0.05, * p<0.1.

Table A.5. Fixed-effect regression of employment variables on cold/heat waves and PM2.5

Explanatory variables	All workers		Self-employed workers		Wage-earning workers	
	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings
	(1)	(2)	(3)	(4)	(5)	(6)
PM 2.5 (μg/m3)	0.0042***	0.0019**	0.0039***	0.0040***	0.0043***	0.0021***
	(0.0004)	(0.0008)	(0.0005)	(0.0013)	(0.0004)	(0.0005)
Number of days with at least 3 consecutive days below the 5th temperature percentile	0.0065***	-0.0030**	0.0056***	-0.0036*	0.0079***	-0.0015**
	(0.0006)	(0.0014)	(0.0006)	(0.0021)	(0.0008)	(0.0006)
Number of days with at least 3 consecutive days above the 95th temperature percentile	-0.0024***	-0.0045***	-0.0014***	-0.0060***	-0.0036***	-0.0044***
	(0.0004)	(0.0009)	(0.0003)	(0.0013)	(0.0006)	(0.0007)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	14.0952***	6.5471***	13.9617***	8.4898***	14.7711***	9.9544***
	(0.7696)	(1.5795)	(0.8230)	(2.2420)	(0.9066)	(1.1819)
Observations	3,583,824	3,583,824	2,053,021	2,053,021	1,530,803	1,530,803
R-squared	0.095	0.184	0.134	0.195	0.068	0.134

Note: This table reports fixed-effect regression of employment on PM2.5, temperature variables, and other control variables. Individual-level control variables include age, age squared, gender, education level dummies, and urban dummy of individuals. District-level control variables include monthly precipitation, wind speed, air pressure, thermal inversion, and humidity.
Robust standard errors in parentheses. The standard errors are clustered at the district level.
*** p<0.01, ** p<0.05, * p<0.1.

Table A.6. 2SLS regression of employment variables on cold/heat waves defined at least 5 consecutive days

Explanatory variables	All workers		Self-employed workers		Wage-earning workers	
	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings
	(1)	(2)	(3)	(4)	(5)	(6)
PM 2.5 (μg/m3)	-0.0108***	-0.0163***	-0.0082***	-0.0135**	-0.0136***	-0.0107***
	(0.0017)	(0.0042)	(0.0020)	(0.0066)	(0.0018)	(0.0021)
Number of days with at least 5 consecutive days below the 5th temperature percentile	0.0083***	0.0013	0.0073***	0.0012	0.0096***	0.0007
	(0.0009)	(0.0019)	(0.0008)	(0.0027)	(0.0012)	(0.0009)
Number of days with at least 5 consecutive days above the 95th temperature percentile	-0.0030***	-0.0041***	-0.0021***	-0.0053***	-0.0041***	-0.0043***
	(0.0004)	(0.0010)	(0.0004)	(0.0015)	(0.0005)	(0.0006)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.8833	-8.3094***	4.9461***	-4.4826	-1.1063	-1.4716
	(1.1678)	(3.0949)	(1.3647)	(4.9004)	(1.3855)	(1.6158)
Observations	3,583,824	3,583,824	2,053,021	2,053,021	1,530,803	1,530,803

Note: This table reports 2SLS regression of employment on PM2.5, temperature variables, and other control variables. The instrumental variable for PM2.5 is wind direction dummies. Individual-level control variables include age, age squared, gender, education level dummies, and urban dummy of individuals. District-level control variables include monthly precipitation, wind speed, air pressure, thermal inversion, and humidity.
Robust standard errors in parentheses. The standard errors are clustered at the district level.
*** p<0.01, ** p<0.05, * p<0.1.

Table A.7. 2SLS regression of employment variables on cold/heat waves defined at least 7 consecutive days

Explanatory variables	All workers		Self-employed workers		Wage-earning workers	
	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings
	(1)	(2)	(3)	(4)	(5)	(6)
PM 2.5 (µg/m3)	-0.0106***	-0.0158***	-0.0079***	-0.0125*	-0.0135***	-0.0102***
	(0.0017)	(0.0041)	(0.0019)	(0.0065)	(0.0018)	(0.0021)
Number of days with at least 7 consecutive days below the 5th temperature percentile	0.0080***	0.0027	0.0074***	0.0042	0.0088***	0.0014
	(0.0009)	(0.0021)	(0.0009)	(0.0031)	(0.0012)	(0.0009)
Number of days with at least 7 consecutive days above the 95th temperature percentile	-0.0026***	-0.0033***	-0.0017***	-0.0041***	-0.0037***	-0.0036***
	(0.0003)	(0.0010)	(0.0004)	(0.0014)	(0.0004)	(0.0006)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.4689	-8.5834***	4.7000***	-4.6449	-1.7944	-1.7346
	(1.1762)	(3.1463)	(1.3726)	(4.9580)	(1.3943)	(1.6568)
Observations	3,583,824	3,583,824	2,053,021	2,053,021	1,530,803	1,530,803

Note: This table reports 2SLS regression of employment on PM2.5, temperature variables, and other control variables. The instrumental variable for PM2.5 is wind direction dummies. Individual-level control variables include age, age squared, gender, education level dummies, and urban dummy of individuals. District-level control variables include monthly precipitation, wind speed, air pressure, thermal inversion, and humidity.
Robust standard errors in parentheses. The standard errors are clustered at the district level.
*** p<0.01, ** p<0.05, * p<0.1.

Table A.8. First-stage regression of PM2.5 during the past 12 months

Explanatory variables	PM 2.5 (µg/m3)	PM 2.5 (µg/m3)	PM 2.5 (µg/m3)	PM 2.5 (µg/m3)
	(1)	(2)	(3)	(4)
Wind direct degree [45, 90)	0.3914	0.3857	0.2029	0.4446
	(0.3649)	(0.3508)	(0.3550)	(0.3668)
Wind direct degree [90, 135)	-0.2700	-0.3186	-0.4623	-0.3646
	(0.3493)	(0.3341)	(0.3426)	(0.3519)
Wind direct degree [135, 180)	-0.5783*	-0.6290*	-0.7487**	-0.6705*
	(0.3407)	(0.3251)	(0.3342)	(0.3432)
Wind direct degree [180, 225)	-0.8830***	-0.9279***	-1.0285***	-0.9864***
	(0.3387)	(0.3237)	(0.3333)	(0.3429)
Wind direct degree [225, 270)	-0.7255**	-0.7723**	-0.8283**	-0.7411**
	(0.3371)	(0.3222)	(0.3309)	(0.3400)
Number of days below the 5th temperature percentile	-0.0363*** (0.0047)			
Number of days above the 95th temperature percentile	-0.0101*** (0.0012)			
Number of days with at least 3 consecutive days below the 5th temperature percentile		-0.0367*** (0.0033)		
Number of days with at least 3 consecutive days above the 95th temperature percentile		-0.0113*** (0.0013)		
Number of days with at least 5 consecutive days below the 5th temperature percentile			-0.0362*** (0.0036)	
Number of days with at least 5 consecutive days above the 95th temperature percentile			-0.0128*** (0.0013)	
Number of days with at least 7 consecutive days below the 5th temperature percentile				-0.0420*** (0.0043)
Number of days with at least 7 consecutive days above the 95th temperature percentile				-0.0105*** (0.0011)
Control variables	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Constant	2,165.98***	2,157.78***	2,109.49***	2,010.34***
	(75.55)	(76.15)	(70.87)	(64.06)
Observations	4,869,818	4,869,818	4,869,818	4,869,818
R-squared	0.983	0.983	0.983	0.983
Cragg Donald Wald *F* statistic	5557.34	5473.63	5705.98	5868.25
Effective *F* statistic	25.62	25.72	26.59	27.12

Note: This table reports fixed-effect regression of the average PM2.5 during the past 12 months on wind direction dummies, temperature variables, and other control variables. Individual-level control variables include age, age squared, gender, education level dummies, and urban dummy of individuals. District-level control variables include monthly precipitation, wind speed, air pressure, thermal inversion, and humidity.
Robust standard errors in parentheses. The standard errors are clustered at the district level.
*** p<0.01, ** p<0.05, * p<0.1.

Table A.9. 2SLS regression of employment variables on cold/heat waves and PM2.5 during the past 12 months

Explanatory variables	Dependent variables							
	Labor force participation (yes=1, no=0)	Having a work (yes=1, no=0)	Having a self-employed work (yes=1, no=0)	Having a wage-earning job (yes=1, no=0)	Labor force participation (yes=1, no=0)	Having a work (yes=1, no=0)	Having a self-employed work (yes=1, no=0)	Having a wage-earning job (yes=1, no=0)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PM 2.5 (µg/m3)	0.0038	0.0052	-0.0016	-0.0000	0.0034	0.0045	-0.0015	-0.0006
	(0.0059)	(0.0061)	(0.0073)	(0.0067)	(0.0054)	(0.0056)	(0.0067)	(0.0062)
Number of days with at least 5 consecutive days below the 5th temperature percentile	0.0002	0.0003	-0.0006**	0.0005*				
	(0.0002)	(0.0002)	(0.0003)	(0.0003)				
Number of days with at least 5 consecutive days above the 95th temperature percentile	0.0001	0.0002	-0.0003***	0.0003***				
	(0.0001)	(0.0001)	(0.0001)	(0.0001)				
Number of days with at least 7 consecutive days below the 5th temperature percentile					0.0003	0.0004	-0.0005	0.0005*
					(0.0002)	(0.0002)	(0.0003)	(0.0003)
Number of days with at least 7 consecutive days above the 95th temperature percentile					0.0001	0.0002**	-0.0002**	0.0002***
					(0.0001)	(0.0001)	(0.0001)	(0.0001)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-1.8223	-4.2987	36.1719**	-7.4810	-0.2921	-1.9411	35.2931**	-5.3105
	(13.1542)	(13.6614)	(16.2359)	(15.0093)	(11.5830)	(11.9890)	(14.2053)	(13.0810)
Observations	4,869,818	4,869,818	4,869,818	4,869,818	4,869,818	4,869,818	4,869,818	4,869,818

Note: This table reports fixed-effect regression of employment on PM2.5, temperature variables, and other control variables. Individual-level control variables include age, age squared, gender, education level dummies, and urban dummy of individuals. District-level control variables include monthly precipitation, wind speed, air pressure, thermal inversion, and humidity.
Robust standard errors in parentheses. The standard errors are clustered at the district level.
*** p<0.01, ** p<0.05, * p<0.1.

Table A.10. Fixed-effect regression of employment variables on extreme temperatures and PM2.5 during the past 12 months

Explanatory variables	Dependent variables							
	Labor force participation (yes=1, no=0)	Having a work (yes=1, no=0)	Having a self-employed work (yes=1, no=0)	Having a wage-earning job (yes=1, no=0)	Labor force participation (yes=1, no=0)	Having a work (yes=1, no=0)	Having a self-employed work (yes=1, no=0)	Having a wage-earning job (yes=1, no=0)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PM 2.5 (µg/m3)	-0.0010**	-0.0011**	-0.0047***	0.0009	-0.0012***	-0.0012***	-0.0050***	0.0012*
	(0.0004)	(0.0005)	(0.0010)	(0.0006)	(0.0004)	(0.0005)	(0.0010)	(0.0006)
Number of days below the 5th percentile of temperature distribution	0.0002***	0.0003***	-0.0003***	0.0003***				
	(0.0001)	(0.0001)	(0.0001)	(0.0001)				
Number of days above the 95th percentile of temperature distribution	0.0000	0.0001*	-0.0005***	0.0004***				
	(0.0001)	(0.0001)	(0.0001)	(0.0001)				
Number of days with at least 3 consecutive days below the 5th temperature percentile					0.0002**	0.0002***	-0.0005***	0.0005***
					(0.0001)	(0.0001)	(0.0001)	(0.0001)
Number of days with at least 3 consecutive days above the 95th temperature percentile					-0.0000	0.0000	-0.0005***	0.0003***
					(0.0001)	(0.0001)	(0.0001)	(0.0001)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	8.9220***	9.3113***	46.6580***	-12.205***	9.4600***	9.8500***	46.4225***	-11.519***
	(2.3309)	(2.4374)	(4.2953)	(2.5278)	(2.3302)	(2.4341)	(4.3034)	(2.5164)
Observations	4,869,818	4,869,818	4,869,818	4,869,818	4,869,818	4,869,818	4,869,818	4,869,818
R-squared	0.350	0.340	0.239	0.227	0.350	0.340	0.239	0.227

Note: This table reports fixed-effect regression of employment on PM2.5, temperature variables, and other control variables. Individual-level control variables include age, age squared, gender, education level dummies, and urban dummy of individuals. District-level control variables include monthly precipitation, wind speed, air pressure, thermal inversion, and humidity.
Robust standard errors in parentheses. The standard errors are clustered at the district level.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.11. Fixed-effect regression of employment variables on cold/heat waves and PM2.5 during the past 12 months

Explanatory variables	Dependent variables							
	Labor force participation (yes=1, no=0)	Having a work (yes=1, no=0)	Having a self-employed work (yes=1, no=0)	Having a wage-earning job (yes=1, no=0)	Labor force participation (yes=1, no=0)	Having a work (yes=1, no=0)	Having a self-employed work (yes=1, no=0)	Having a wage-earning job (yes=1, no=0)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PM 2.5 (µg/m3)	-0.0012***	-0.0013***	-0.0054***	0.0014**	-0.0012***	-0.0012***	-0.0051***	0.0013**
	(0.0005)	(0.0005)	(0.0010)	(0.0007)	(0.0004)	(0.0005)	(0.0010)	(0.0007)
Number of days with at least 5 consecutive days below the 5th temperature percentile	0.0001	0.0001	-0.0007***	0.0006***				
	(0.0001)	(0.0001)	(0.0001)	(0.0001)				
Number of days with at least 5 consecutive days above the 95th temperature percentile	0.0000	0.0001	-0.0004***	0.0003***				
	(0.0001)	(0.0001)	(0.0001)	(0.0001)				
Number of days with at least 7 consecutive days below the 5th temperature percentile					0.0001	0.0001	-0.0006***	0.0006***
					(0.0001)	(0.0001)	(0.0001)	(0.0001)
Number of days with at least 7 consecutive days above the 95th temperature percentile					0.0001	0.0001**	-0.0003***	0.0003***
					(0.0000)	(0.0001)	(0.0001)	(0.0001)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	8.9770***	9.4736***	43.6484***	-10.2185***	8.9638***	9.6572***	41.8815***	-8.9148***
	(2.2438)	(2.3327)	(4.1281)	(2.4381)	(2.2035)	(2.2760)	(4.0552)	(2.4015)
Observations	4,869,818	4,869,818	4,869,818	4,869,818	4,869,818	4,869,818	4,869,818	4,869,818
R-squared	0.350	0.340	0.239	0.227	0.350	0.340	0.239	0.227

Note: This table reports fixed-effect regression of employment on PM2.5, temperature variables, and other control variables. Individual-level control variables include age, age squared, gender, education level dummies, and urban dummy of individuals. District-level control variables include monthly precipitation, wind speed, air pressure, thermal inversion, and humidity.
Robust standard errors in parentheses. The standard errors are clustered at the district level.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.12. 2SLS regression of employment variables on extreme temperatures and PM2.5 (small specification model)

Explanatory variables	All workers		Self-employed workers		Wage-earning workers	
	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings
	(1)	(2)	(3)	(4)	(5)	(6)
PM 2.5 (µg/m3)	-0.0087***	-0.0114***	-0.0072***	-0.0101**	-0.0119***	-0.0083***
	(0.0014)	(0.0033)	(0.0014)	(0.0045)	(0.0017)	(0.0019)
Number of days below the 5th temperature percentile	0.0100***	0.0002	0.0085***	-0.0007	0.0125***	0.0013
	(0.0009)	(0.0021)	(0.0008)	(0.0028)	(0.0013)	(0.0010)
Number of days above the 95th temperature percentile	-0.0009***	-0.0035***	-0.0000	-0.0044***	-0.0022***	-0.0025***
	(0.0003)	(0.0009)	(0.0003)	(0.0012)	(0.0005)	(0.0006)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.4849***	4.0122***	3.0878***	-2.0107***	4.1401***	8.1403***
	(0.0700)	(0.2395)	(0.0680)	(0.2605)	(0.0856)	(0.1101)
Observations	3,583,824	3,583,824	2,053,021	2,053,021	1,530,803	1,530,803

Note: This table reports 2SLS regression of employment on PM2.5, temperature variables, age and gender. The instrumental variable for PM2.5 is wind direction dummies. The control variables only include age, age squared, and gender of individuals.

Robust standard errors in parentheses. The standard errors are clustered at the district level.

*** p<0.01, ** p<0.05, * p<0.1.

Table A.13. 2SLS regression of employment variables on cold/heat waves and PM2.5 (small specification model)

Explanatory variables	All workers		Self-employed workers		Wage-earning workers	
	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings
	(1)	(2)	(3)	(4)	(5)	(6)
PM 2.5 (µg/m3)	-0.0087***	-0.0114***	-0.0073***	-0.0101**	-0.0117***	-0.0083***
	(0.0013)	(0.0032)	(0.0014)	(0.0044)	(0.0016)	(0.0019)
Number of days with at least 3 consecutive days below the 5th temperature percentile	0.0119***	0.0029	0.0098***	0.0013	0.0154***	0.0041***
	(0.0010)	(0.0022)	(0.0009)	(0.0028)	(0.0014)	(0.0013)
Number of days with at least 3 consecutive days above the 95th temperature percentile	-0.0006**	-0.0031***	0.0002	-0.0039***	-0.0017***	-0.0023***
	(0.0003)	(0.0009)	(0.0003)	(0.0012)	(0.0004)	(0.0005)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.4859***	3.9998***	3.0939***	-2.0224***	4.1300***	8.1277***
	(0.0686)	(0.2362)	(0.0674)	(0.2588)	(0.0820)	(0.1065)
Observations	3,583,824	3,583,824	2,053,021	2,053,021	1,530,803	1,530,803

Note: This table reports 2SLS regression of employment on PM2.5, temperature variables, and age and gender. The instrumental variable for PM2.5 is wind direction dummies. The control variables only include age, age squared, and gender of individuals.
Robust standard errors in parentheses. The standard errors are clustered at the district level.
*** p<0.01, ** p<0.05, * p<0.1.

Table A.14. 2SLS regression of employment variables on extreme temperatures and PM2.5 with control for province-month fixed effects

Explanatory variables	All workers		Self-employed workers		Wage-earning workers	
	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings
	(1)	(2)	(3)	(4)	(5)	(6)
PM 2.5 (µg/m3)	-0.0122***	-0.0133***	-0.0112***	-0.0142**	-0.0119***	-0.0039*
	(0.0018)	(0.0043)	(0.0020)	(0.0066)	(0.0021)	(0.0022)
Number of days below the 5th temperature percentile	0.0120***	0.0025	0.0104***	0.0036	0.0133***	-0.0007
	(0.0010)	(0.0023)	(0.0009)	(0.0032)	(0.0013)	(0.0011)
Number of days above the 95th temperature percentile	-0.0074***	-0.0090***	-0.0055***	-0.0114***	-0.0095***	-0.0065***
	(0.0007)	(0.0017)	(0.0007)	(0.0024)	(0.0008)	(0.0010)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Province-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	27.0980***	25.3580***	25.8984***	37.1057***	30.2364***	7.4056***
	(1.5391)	(3.0317)	(1.6802)	(4.5606)	(1.9160)	(1.5769)
Observations	3,583,824	3,583,824	2,053,021	2,053,021	1,530,803	1,530,803

Note: This table reports 2SLS regression of employment on PM2.5, temperature variables, age and gender. The instrumental variable for PM2.5 is wind direction dummies. The control variables only include age, age squared, and gender of individuals.
Robust standard errors in parentheses. The standard errors are clustered at the district level.
*** p<0.01, ** p<0.05, * p<0.1.

Table A.15. 2SLS regression of employment variables on cold/heat waves and PM2.5 with control for province-month fixed effects

Explanatory variables	All workers		Self-employed workers		Wage-earning workers	
	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings
	(1)	(2)	(3)	(4)	(5)	(6)
PM 2.5 (μg/m3)	-0.0116***	-0.0130***	-0.0106***	-0.0135**	-0.0113***	-0.0037*
	(0.0017)	(0.0042)	(0.0019)	(0.0064)	(0.0021)	(0.0022)
Number of days with at least 3 consecutive days below the 5th temperature percentile	0.0133***	0.0043*	0.0112***	0.0046	0.0155***	0.0015
	(0.0010)	(0.0023)	(0.0010)	(0.0032)	(0.0014)	(0.0012)
Number of days with at least 3 consecutive days above the 95th temperature percentile	-0.0060***	-0.0072***	-0.0045***	-0.0092***	-0.0076***	-0.0056***
	(0.0006)	(0.0015)	(0.0006)	(0.0022)	(0.0007)	(0.0009)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Province-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	25.3850***	23.9820***	24.6105***	35.1878***	27.9665***	6.9112***
	(1.4545)	(2.9009)	(1.6124)	(4.4199)	(1.8099)	(1.4889)
Observations	3,583,824	3,583,824	2,053,021	2,053,021	1,530,803	1,530,803

Note: This table reports 2SLS regression of employment on PM2.5, temperature variables, and age and gender. The instrumental variable for PM2.5 is wind direction dummies. The control variables only include age, age squared, and gender of individuals.
Robust standard errors in parentheses. The standard errors are clustered at the district level.
*** p<0.01, ** p<0.05, * p<0.1.

Table A.16. 2SLS regression of employment variables on extreme temperatures and PM2.5 (the sample of people aged 15-64)

Explanatory variables	All workers		Self-employed workers		Wage-earning workers	
	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings
	(1)	(2)	(3)	(4)	(5)	(6)
PM 2.5 (µg/m3)	-0.0119***	-0.0178***	-0.0092***	-0.0155**	-0.0144***	-0.0118***
	(0.0018)	(0.0044)	(0.0021)	(0.0070)	(0.0019)	(0.0022)
Number of days below the 5th temperature percentile	0.0109***	0.0024	0.0090***	0.0019	0.0131***	0.0020*
	(0.0011)	(0.0023)	(0.0010)	(0.0033)	(0.0014)	(0.0012)
Number of days above the 95th temperature percentile	-0.0046***	-0.0073***	-0.0032***	-0.0091***	-0.0062***	-0.0059***
	(0.0005)	(0.0011)	(0.0005)	(0.0016)	(0.0007)	(0.0008)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.6972**	-8.5330***	5.2810***	-5.3499	0.7000	-0.6836
	(1.1555)	(2.9843)	(1.3692)	(4.8817)	(1.3534)	(1.5299)
Observations	3,419,877	3,419,877	1,903,341	1,903,341	1,516,536	1,516,536

Note: This table reports 2SLS regression of employment on PM2.5, temperature variables, age and gender. The instrumental variable for PM2.5 is wind direction dummies. Individual-level control variables include age, age squared, gender, education level dummies, and urban dummy of individuals. District-level control variables include monthly precipitation, wind speed, air pressure, thermal inversion, and humidity.
Robust standard errors in parentheses. The standard errors are clustered at the district level.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.17. 2SLS regression of employment variables on cold/heat waves and PM2.5 (the sample of people aged 15-64)

Explanatory variables	All workers		Self-employed workers		Wage-earning workers	
	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings
	(1)	(2)	(3)	(4)	(5)	(6)
PM 2.5 (µg/m3)	-0.0113***	-0.0170***	-0.0088***	-0.0146**	-0.0136***	-0.0111***
	(0.0017)	(0.0042)	(0.0020)	(0.0068)	(0.0018)	(0.0021)
Number of days with at least 3 consecutive days below the 5th temperature percentile	0.0123***	0.0044*	0.0099***	0.0034	0.0154***	0.0040***
	(0.0011)	(0.0023)	(0.0010)	(0.0032)	(0.0015)	(0.0013)
Number of days with at least 3 consecutive days above the 95th temperature percentile	-0.0039***	-0.0065***	-0.0028***	-0.0081***	-0.0052***	-0.0055***
	(0.0004)	(0.0011)	(0.0004)	(0.0015)	(0.0006)	(0.0007)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.4587**	-8.7346***	5.0977***	-5.7220	0.3688	-0.5635
	(1.1590)	(3.0061)	(1.3705)	(4.9079)	(1.3576)	(1.5369)
Observations	3,419,877	3,419,877	1,903,341	1,903,341	1,516,536	1,516,536

Note: This table reports 2SLS regression of employment on PM2.5, temperature variables, and age and gender. The instrumental variable for PM2.5 is wind direction dummies. Individual-level control variables include age, age squared, gender, education level dummies, and urban dummy of individuals. District-level control variables include monthly precipitation, wind speed, air pressure, thermal inversion, and humidity.
Robust standard errors in parentheses. The standard errors are clustered at the district level.
*** p<0.01, ** p<0.05, * p<0.1.

Table A.18. 2SLS regression of employment variables on extreme temperatures and PM2.5 (without the sampling weight)

Explanatory variables	All workers		Self-employed workers		Wage-earning workers	
	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings
	(1)	(2)	(3)	(4)	(5)	(6)
PM 2.5 (µg/m3)	-0.0108***	-0.0126***	-0.0083***	-0.0101	-0.0139***	-0.0108***
	(0.0017)	(0.0045)	(0.0021)	(0.0069)	(0.0018)	(0.0021)
Number of days below the 5th temperature percentile	0.0098***	-0.0011	0.0082***	-0.0017	0.0121***	0.0020**
	(0.0009)	(0.0021)	(0.0009)	(0.0030)	(0.0011)	(0.0010)
Number of days above the 95th temperature percentile	-0.0034***	-0.0066***	-0.0022***	-0.0093***	-0.0051***	-0.0040***
	(0.0005)	(0.0011)	(0.0005)	(0.0015)	(0.0006)	(0.0005)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.8343**	-4.8268	5.9020***	-0.3383	-0.3645	-1.0609
	(1.1976)	(3.1606)	(1.4217)	(4.7389)	(1.3694)	(1.5199)
Observations	3,583,824	3,583,824	2,053,021	2,053,021	1,530,803	1,530,803

Note: This table reports 2SLS regression of employment on PM2.5, temperature variables, age and gender. The instrumental variable for PM2.5 is wind direction dummies. Individual-level control variables include age, age squared, gender, education level dummies, and urban dummy of individuals. District-level control variables include monthly precipitation, wind speed, air pressure, thermal inversion, and humidity.
Robust standard errors in parentheses. The standard errors are clustered at the district level.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.19. 2SLS regression of employment variables on cold/heat waves and PM2.5 (without the sampling weight)

Explanatory variables	All workers		Self-employed workers		Wage-earning workers	
	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings
	(1)	(2)	(3)	(4)	(5)	(6)
PM 2.5 (μg/m3)	-0.0102***	-0.0123***	-0.0079***	-0.0098	-0.0132***	-0.0102***
	(0.0016)	(0.0044)	(0.0020)	(0.0067)	(0.0017)	(0.0020)
Number of days with at least 3 consecutive days below the 5th temperature percentile	0.0109***	-0.0003	0.0091***	-0.0011	0.0139***	0.0030***
	(0.0009)	(0.0021)	(0.0009)	(0.0030)	(0.0011)	(0.0010)
Number of days with at least 3 consecutive days above the 95th temperature percentile	-0.0028***	-0.0064***	-0.0018***	-0.0090***	-0.0042***	-0.0038***
	(0.0004)	(0.0010)	(0.0005)	(0.0015)	(0.0005)	(0.0005)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.6417**	-5.1126	5.7851***	-0.9025	-0.6703	-0.9703
	(1.1924)	(3.1679)	(1.4153)	(4.7505)	(1.3630)	(1.5222)
Observations	3,583,824	3,583,824	2,053,021	2,053,021	1,530,803	1,530,803

Note: This table reports 2SLS regression of employment on PM2.5, temperature variables, and age and gender. The instrumental variable for PM2.5 is wind direction dummies. Individual-level control variables include age, age squared, gender, education level dummies, and urban dummy of individuals. District-level control variables include monthly precipitation, wind speed, air pressure, thermal inversion, and humidity.
Robust standard errors in parentheses. The standard errors are clustered at the district level.
*** p<0.01, ** p<0.05, * p<0.1.

Table A.20. 2SLS regression of employment variables on extreme temperatures and PM2.5 ((standard errors are clustered et the enumeration area level)

Explanatory variables	All workers		Self-employed workers		Wage-earning workers	
	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings
	(1)	(2)	(3)	(4)	(5)	(6)
PM 2.5 (µg/m3)	-0.0115***	-0.0172***	-0.0086***	-0.0146***	-0.0144***	-0.0119***
	(0.0012)	(0.0034)	(0.0016)	(0.0055)	(0.0014)	(0.0017)
Number of days below the 5th temperature percentile	0.0107***	0.0018	0.0087***	0.0008	0.0130***	0.0020**
	(0.0007)	(0.0018)	(0.0008)	(0.0026)	(0.0010)	(0.0009)
Number of days above the 95th temperature percentile	-0.0045***	-0.0071***	-0.0030***	-0.0088***	-0.0062***	-0.0060***
	(0.0003)	(0.0009)	(0.0003)	(0.0013)	(0.0004)	(0.0006)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.0974***	-6.6956**	5.7778***	-2.7132	0.6745	-0.7137
	(0.9601)	(2.6943)	(1.1793)	(4.1736)	(1.1702)	(1.5510)
Observations	3,583,824	3,583,824	2,053,021	2,053,021	1,530,803	1,530,803

Note: This table reports 2SLS regression of employment on PM2.5, temperature variables, age and gender. The instrumental variable for PM2.5 is wind direction dummies. Individual-level control variables include age, age squared, gender, education level dummies, and urban dummy of individuals. District-level control variables include monthly precipitation, wind speed, air pressure, thermal inversion, and humidity.
Robust standard errors in parentheses. The standard errors are clustered at the enumeration area level.
*** p<0.01, ** p<0.05, * p<0.1.

Table A.21. 2SLS regression of employment variables on cold/heat waves and PM2.5 (standard errors are clustered et the enumeration area level)

Explanatory variables	All workers		Self-employed workers		Wage-earning workers	
	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings
	(1)	(2)	(3)	(4)	(5)	(6)
PM 2.5 (µg/m3)	-0.0109***	-0.0165***	-0.0082***	-0.0138***	-0.0136***	-0.0111***
	(0.0012)	(0.0033)	(0.0016)	(0.0054)	(0.0013)	(0.0017)
Number of days with at least 3 consecutive days below the 5th temperature percentile	0.0121***	0.0037**	0.0096***	0.0022	0.0153***	0.0040***
	(0.0007)	(0.0018)	(0.0008)	(0.0026)	(0.0010)	(0.0010)
Number of days with at least 3 consecutive days above the 95th temperature percentile	-0.0038***	-0.0062***	-0.0026***	-0.0077***	-0.0052***	-0.0056***
	(0.0003)	(0.0009)	(0.0003)	(0.0013)	(0.0004)	(0.0005)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.8470***	-6.9678**	5.5788***	-3.1612	0.3394	-0.5905
	(0.9608)	(2.7063)	(1.1801)	(4.1897)	(1.1718)	(1.5536)
Observations	3,583,824	3,583,824	2,053,021	2,053,021	1,530,803	1,530,803

Note: This table reports 2SLS regression of employment on PM2.5, temperature variables, and age and gender. The instrumental variable for PM2.5 is wind direction dummies. Individual-level control variables include age, age squared, gender, education level dummies, and urban dummy of individuals. District-level control variables include monthly precipitation, wind speed, air pressure, thermal inversion, and humidity.
Robust standard errors in parentheses. The standard errors are clustered at the enumeration area level.
*** p<0.01, ** p<0.05, * p<0.1.

Table A.22. 2SLS regression of employment variables on extreme temperatures and PM2.5 (using heteroskedasticity-consistent standard errors)

Explanatory variables	All workers		Self-employed workers		Wage-earning workers	
	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings
	(1)	(2)	(3)	(4)	(5)	(6)
PM 2.5 (µg/m3)	-0.0115***	-0.0172***	-0.0086***	-0.0146***	-0.0144***	-0.0119***
	(0.0005)	(0.0020)	(0.0007)	(0.0038)	(0.0005)	(0.0008)
Number of days below the 5th temperature percentile	0.0107***	0.0018*	0.0087***	0.0008	0.0130***	0.0020***
	(0.0002)	(0.0011)	(0.0003)	(0.0018)	(0.0003)	(0.0004)
Number of days above the 95th temperature percentile	-0.0045***	-0.0071***	-0.0030***	-0.0088***	-0.0062***	-0.0060***
	(0.0001)	(0.0005)	(0.0002)	(0.0009)	(0.0002)	(0.0002)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.0974***	-6.6956***	5.7778***	-2.7132	0.6745	-0.7137
	(0.3719)	(1.7060)	(0.5472)	(2.9557)	(0.4796)	(0.7373)
Observations	3,583,824	3,583,824	2,053,021	2,053,021	1,530,803	1,530,803

Note: This table reports 2SLS regression of employment on PM2.5, temperature variables, age and gender. The instrumental variable for PM2.5 is wind direction dummies. Individual-level control variables include age, age squared, gender, education level dummies, and urban dummy of individuals. District-level control variables include monthly precipitation, wind speed, air pressure, thermal inversion, and humidity.
Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table A.23. 2SLS regression of employment variables on cold/heat waves and PM2.5 (using heteroskedasticity-consistent standard errors)

Explanatory variables	All workers		Self-employed workers		Wage-earning workers	
	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings	Log of working hours in the past 7 days	Log of monthly earnings
	(1)	(2)	(3)	(4)	(5)	(6)
PM 2.5 (μg/m3)	-0.0109***	-0.0165***	-0.0082***	-0.0138***	-0.0136***	-0.0111***
	(0.0004)	(0.0020)	(0.0007)	(0.0037)	(0.0005)	(0.0008)
Number of days with at least 3 consecutive days below the 5th temperature percentile	0.0121***	0.0037***	0.0096***	0.0022	0.0153***	0.0040***
	(0.0003)	(0.0011)	(0.0003)	(0.0018)	(0.0004)	(0.0004)
Number of days with at least 3 consecutive days above the 95th temperature percentile	-0.0038***	-0.0062***	-0.0026***	-0.0077***	-0.0052***	-0.0056***
	(0.0001)	(0.0005)	(0.0002)	(0.0009)	(0.0002)	(0.0002)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.8470***	-6.9678***	5.5788***	-3.1612	0.3394	-0.5905
	(0.3727)	(1.7115)	(0.5484)	(2.9649)	(0.4811)	(0.7385)
Observations	3,583,824	3,583,824	2,053,021	2,053,021	1,530,803	1,530,803

Note: This table reports 2SLS regression of employment on PM2.5, temperature variables, and age and gender. The instrumental variable for PM2.5 is wind direction dummies. Individual-level control variables include age, age squared, gender, education level dummies, and urban dummy of individuals. District-level control variables include monthly precipitation, wind speed, air pressure, thermal inversion, and humidity.
Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table A.24. 2SLS regression of log of monthly earnings by levels of outdoor and air pollution exposure

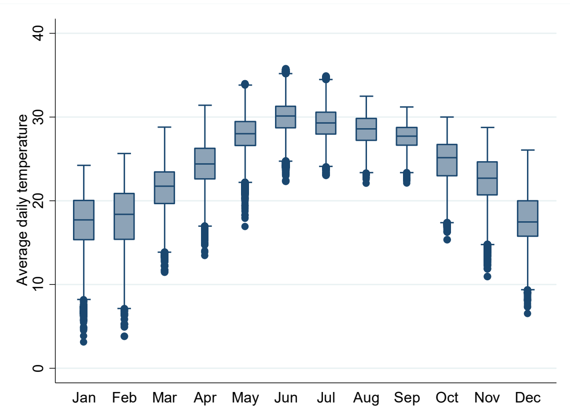
Explanatory variables	Occupations without outdoor exposure	Occupations with moderate outdoor exposure	Medium outdoor exposure occupation	Occupations with high outdoor exposure	Low air pollution exposure	High air pollution exposure
	(1)	(2)	(3)	(4)	(5)	(6)
PM 2.5 (µg/m3)	-0.0066***	-0.0098***	-0.0190***	-0.0114	-0.0128***	-0.0085**
	(0.0025)	(0.0021)	(0.0033)	(0.0095)	(0.0022)	(0.0033)
Number of days below the 5th temperature percentile	-0.0001	0.0002	0.0048***	0.0020	0.0019	0.0017
	(0.0012)	(0.0013)	(0.0015)	(0.0046)	(0.0012)	(0.0017)
Number of days above the 95th temperature percentile	-0.0042***	-0.0059***	-0.0077***	-0.0025*	-0.0059***	-0.0060***
	(0.0011)	(0.0009)	(0.0011)	(0.0013)	(0.0007)	(0.0013)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.6948	-0.1135	-1.6124	0.9311	-1.7929	3.6758
	(2.3323)	(1.6722)	(2.1122)	(5.5224)	(1.5589)	(2.7074)
Observations	180,087	822,742	399,382	128,592	1,217,635	313,168

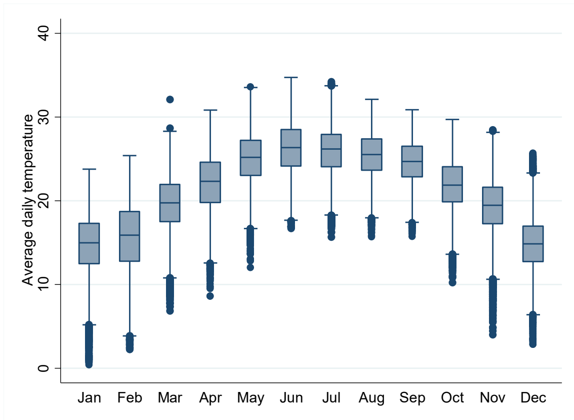
Note: This table reports 2SLS regression of monthly earnings on PM2.5, temperature variables, and other control variables. The instrumental variable for PM2.5 is wind direction dummies. Individual-level control variables include age, age squared, gender, education level dummies, and urban dummy of individuals. District-level control variables include monthly precipitation, wind speed, air pressure, thermal inversion, and humidity.
Robust standard errors in parentheses. The standard errors are clustered at the district level.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Figure A.1: Box plot of daily temperature by months during the 2015-2022 period

Panel A. Red River Delta

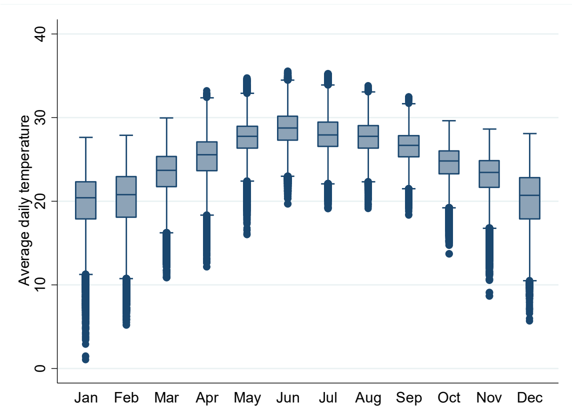
Panel B. Northern Midlands and Mountain Areas

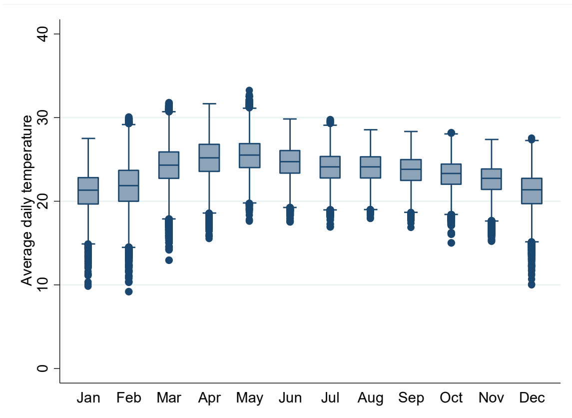




Panel C. North Central and Central coastal areas

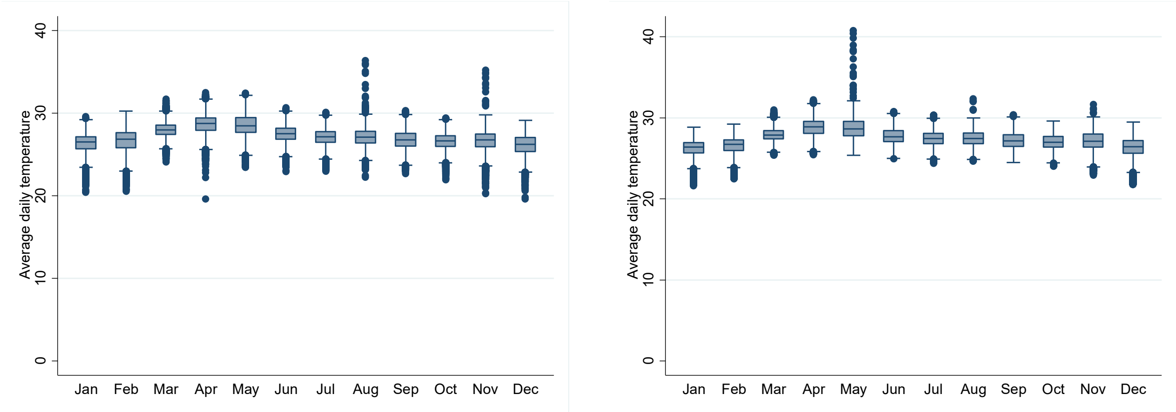
Panel D. Central Highland





Panel E. Southeast

Panel F. Mekong River Delta

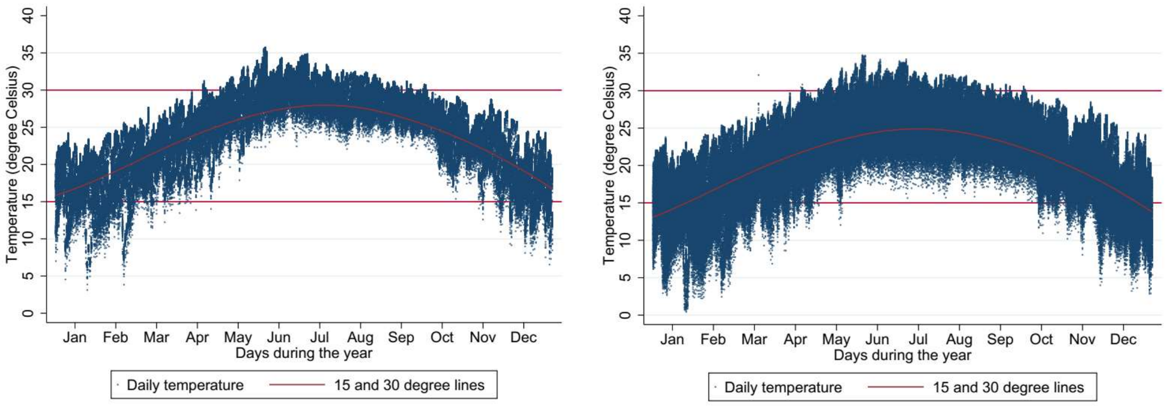


Note: This figure presents the median of daily mean temperature of months over the 2015-2022 period.

Figure A.2. Scatter plot of daily mean temperature during the 2015-2022 period

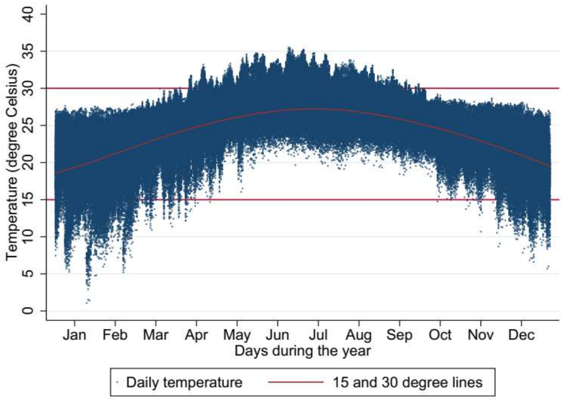
Panel A. Red River Delta

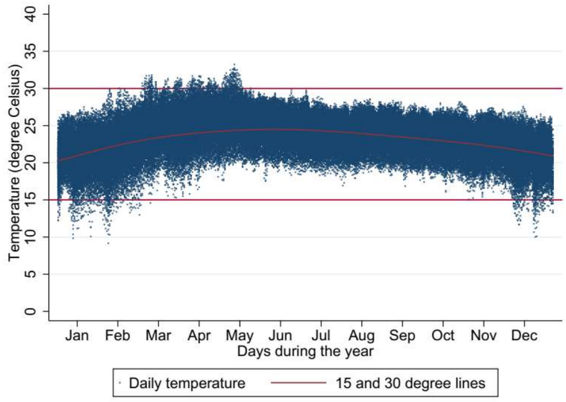
Panel B. Northern Midlands and Mountain Areas



Panel C. North Central and Central coastal areas

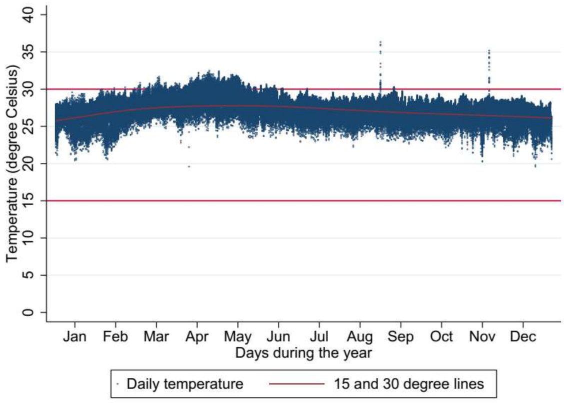
Panel D. Central Highland

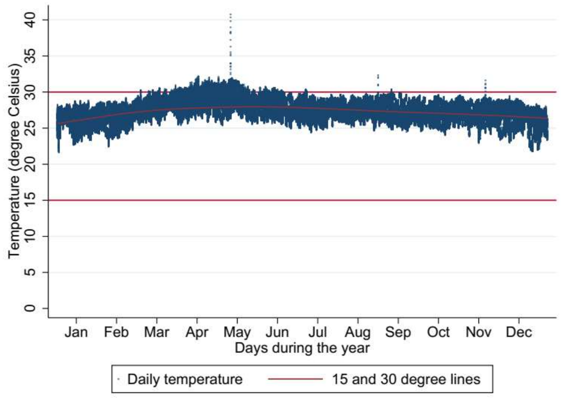




Panel E. Southeast

Panel F. Mekong River Delta



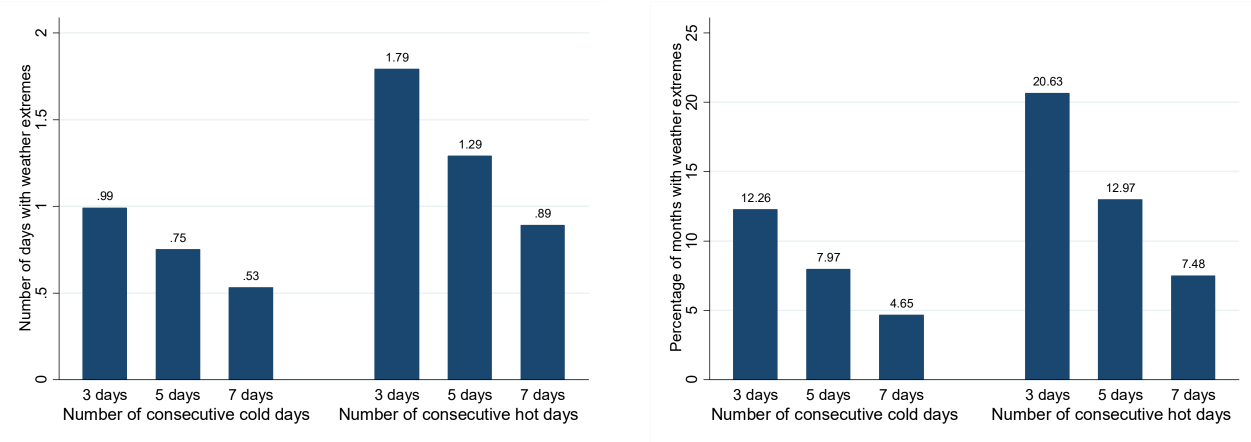


Note: This figure presents the daily mean temperature of districts over the 2015-2022 period.

Figure A.3: Cold and heat waves

Panel A. The average number of consecutive days in cold and heat waves

Panel B. The percentage of months with cold and heat waves

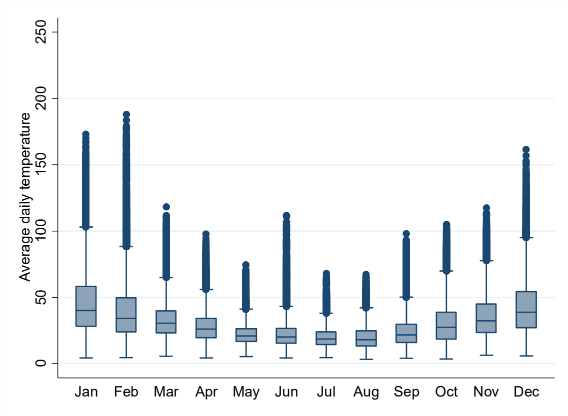


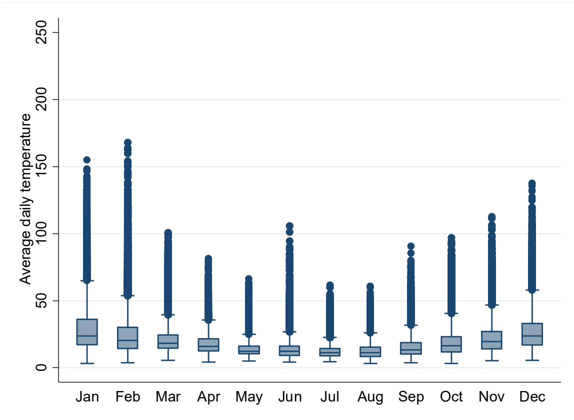
Note: Panel A of this figure presents the average number of days per month in cold and heat waves, defined based on the 5th and 95th percentiles of the district-specific temperature distribution during the past 20 years and varying durations of consecutive days. Panel B presents the average percentage of months in which at least one cold or heat wave (defined on the basis of varying durations of consecutive days) occurred during the 2015-2022 period.

Figure A.4: Box plot of daily PM2.5 by months during the 2015-2022 period

Panel A. Red River Delta

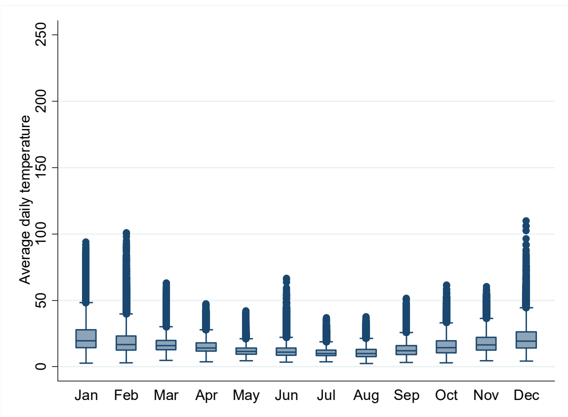
Panel B. Northern Midlands and Mountain Areas

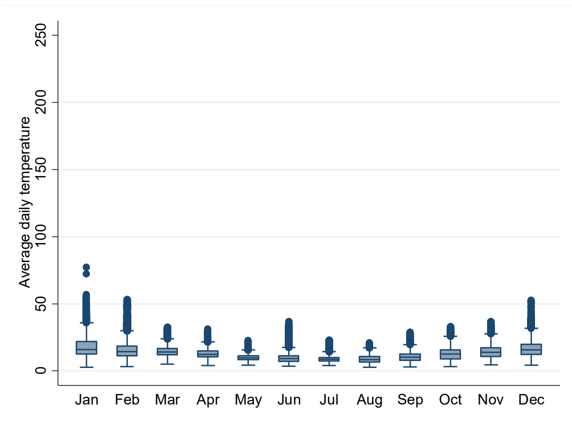




Panel C. North Central and Central coastal areas

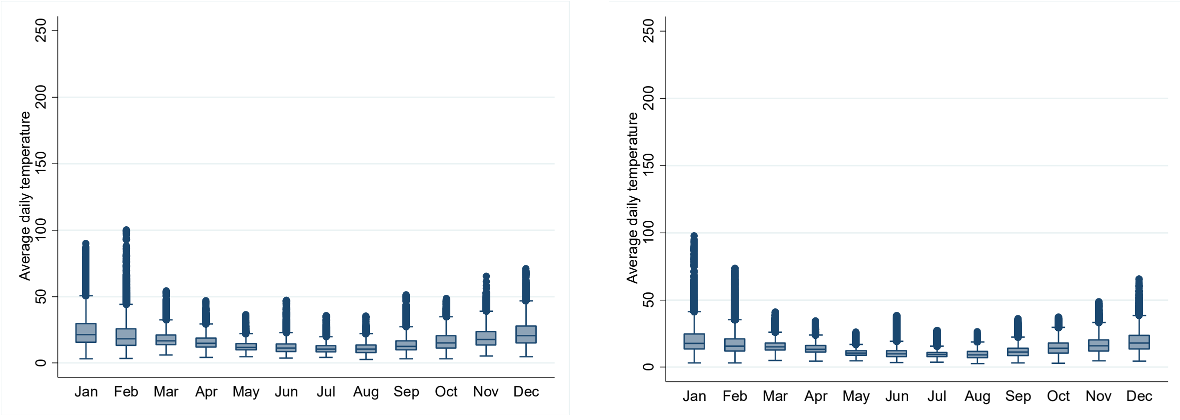
Panel D. Central Highland





Panel E. Southeast

Panel F. Mekong River Delta

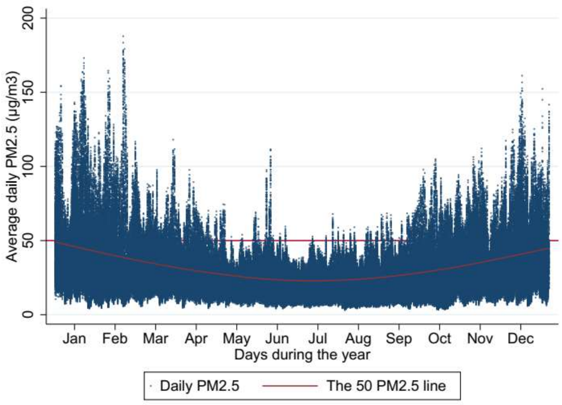


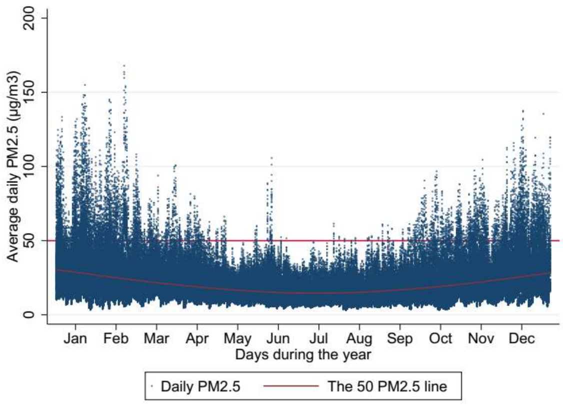
Note: This figure presents the median of daily mean PM2.5 across months over the 2015-2022 period.

Figure A.5. Scatter plot of daily mean PM2.5 of districts during the 2015-2022 period

Panel A. Red River Delta

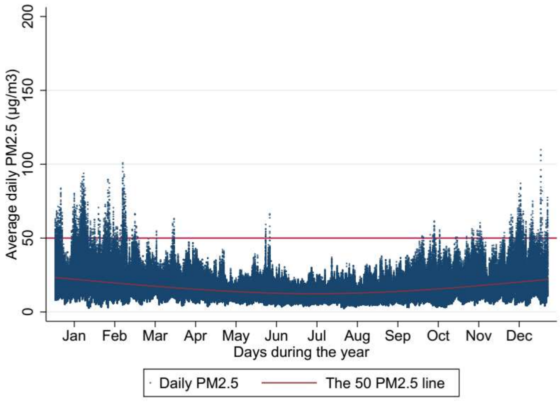
Panel B. Northern Midlands and Mountain Areas

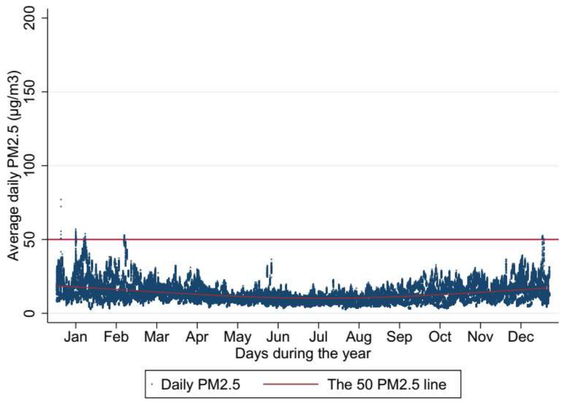




Panel C. North Central and Central coastal areas

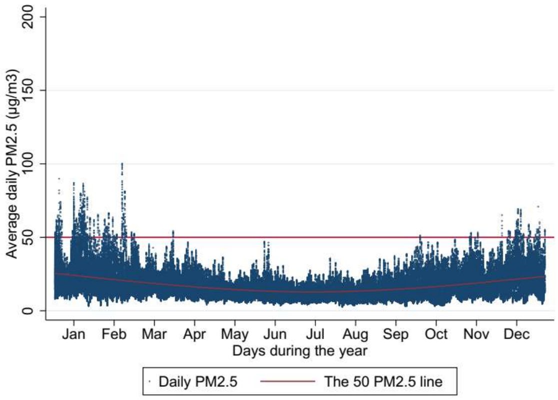
Panel D. Central Highland

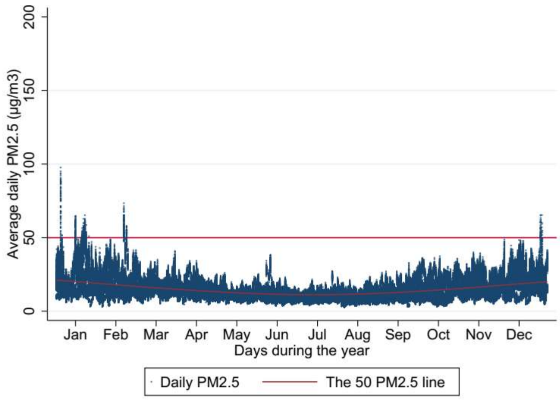




Panel E. Southeast

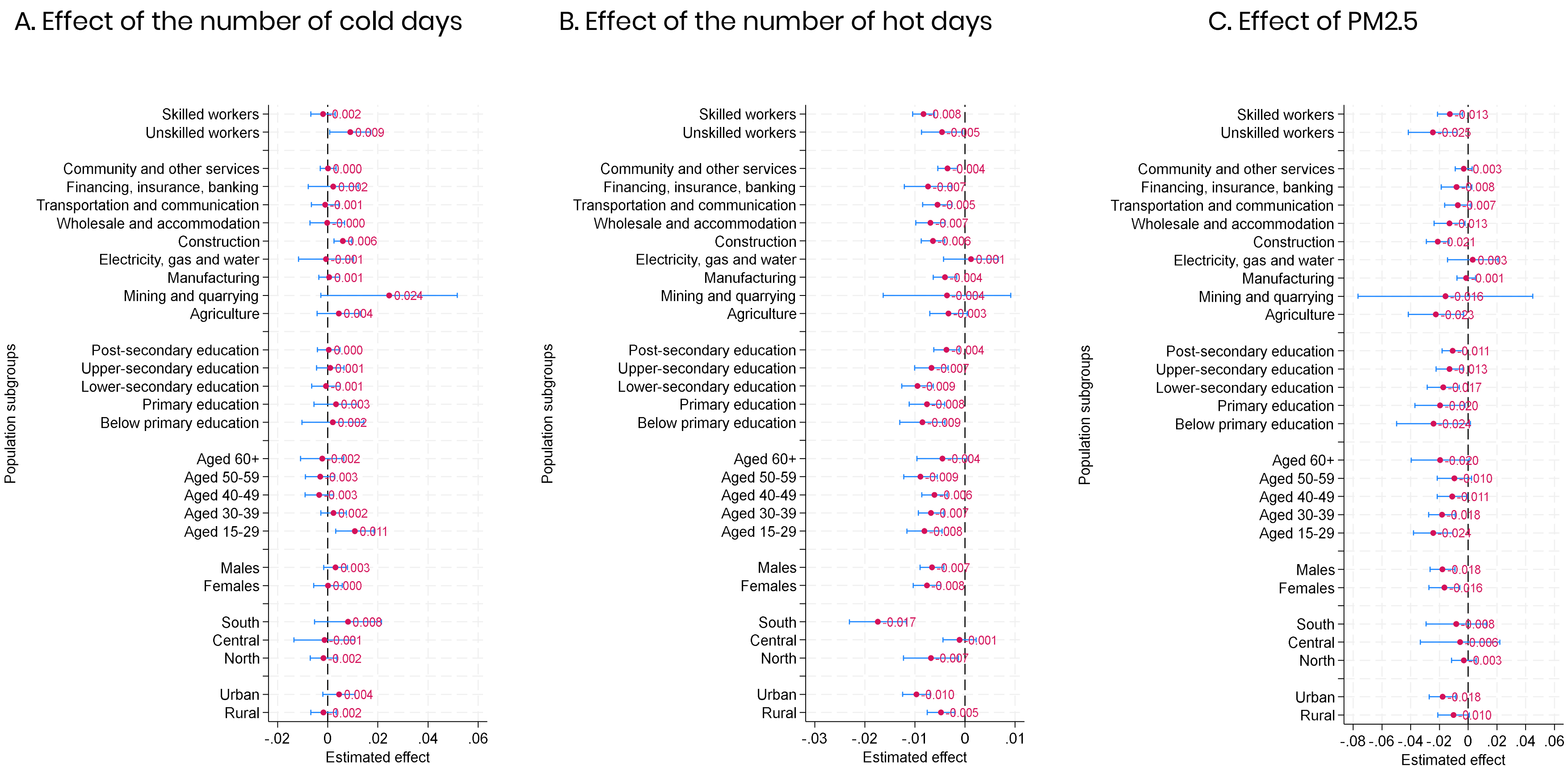
Panel F. Mekong River Delta





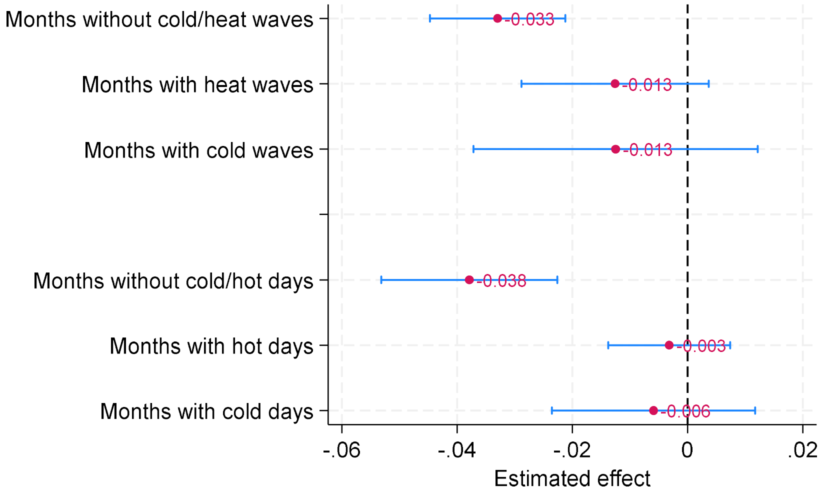
Note: This figure presents the daily mean PM2.5 of districts over the 2015-2022 period.

Figure A.6: The effect of extreme temperatures and air pollution on log of monthly earnings



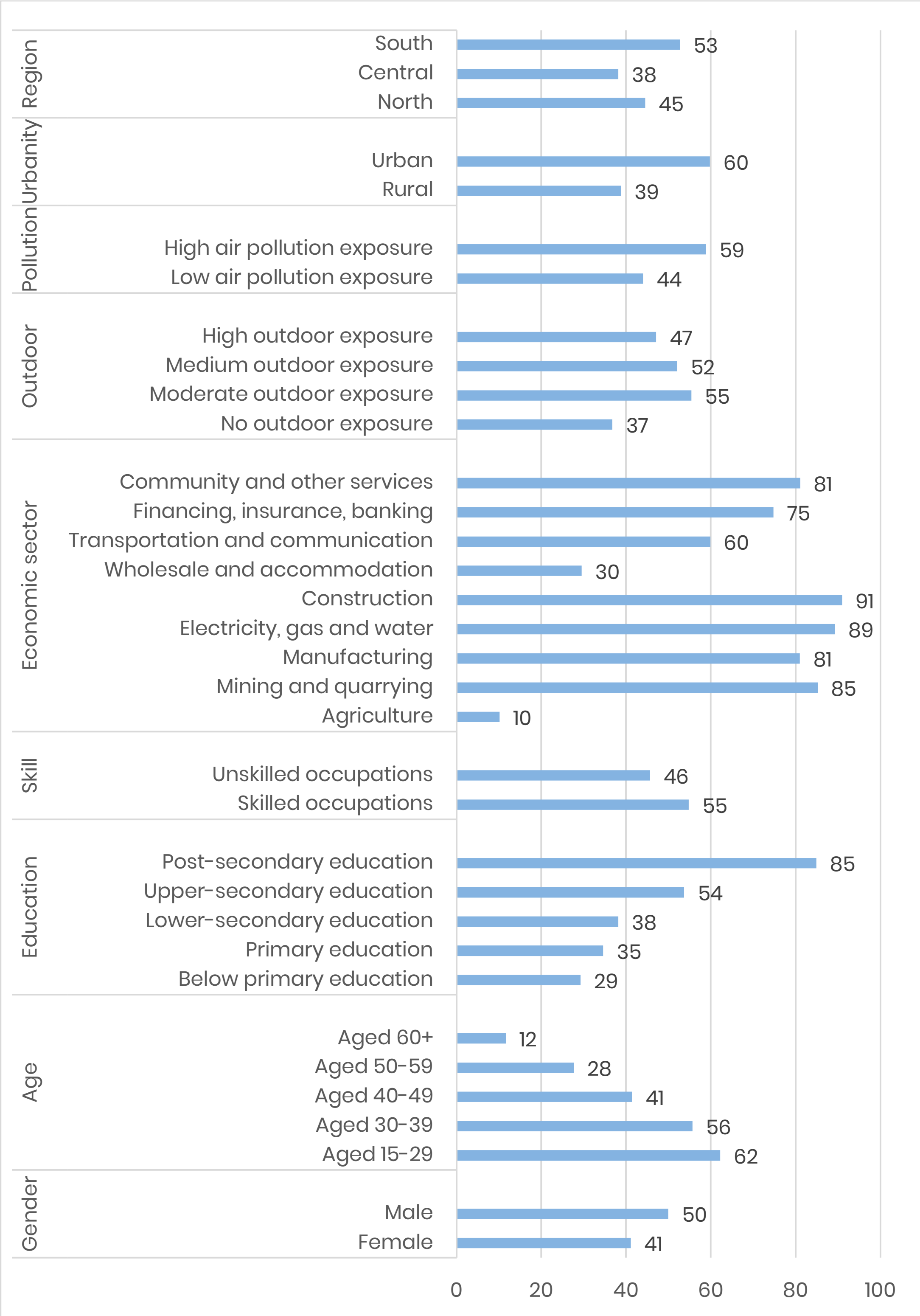
Note: Panels A and B graph the estimates and their 95% confidence intervals of the effect of the number of days below the 5th percentile and the number of days above the 95th percentile of temperature distribution log of monthly earnings of different population sub-groups. Panel C presents the estimates and their 95% confidence intervals of the effect of PM2.5 on log of monthly earnings of different population sub-groups. The model specification is the same as Table 2.

Figure A.7: The effect of PM2.5 on log of monthly earnings during months with and months without temperatures extremes



Note: This figure graphs the estimates and their 95% confidence intervals of the effect of PM2.5 on log of monthly earnings during months with and months without temperatures extremes. The model specification is the same as Table 4.

Figure A.8. Share of wage workers in total employment across population subgroups (percent)



This figure presents estimates of the share of wage workers in total employment (percent) across population subgroups, using pooled data from the 2015–2022 LFSs.

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