The Impact of Air Pollution on Labor Supply in China *

Mingxuan Fan† and Corbett Grainger

Department of Agricultural and Applied Economics, University of Wisconsin-Madison

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Abstract

In this paper, we study the relationship between air pollution, i.e. fine particulate matter ($PM_{2.5}$), and labor hours worked in China. We use restricted individual-level panel data, from the China Family Panel Survey, and match it with sub-district level remote-sensing pollution estimates. Our individual fixed effects estimates indicate that, among the population aged 16-75, an increase of 1 $\mu g/m^3$ in $PM_{2.5}$ reduces an individual's average hours worked by 29 minutes per week. Evaluated at the mean in our data, a one percent increase in annual average $PM_{2.5}$ concentrations decreases hours worked by about one percent. This suggests that chronic pollution exposure has a significant impact on labor supply decisions.

Keywords: labor hours; air pollution; China.

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†Corresponding author: mingxuan.fan@wisc.edu

1 Introduction

Due to its rapid economic growth and corresponding increase in fossil fuel use, air pollution, especially fine particulate matter ($PM_{2.5}$), has become a major concern in China. The annual average population-weighted $PM_{2.5}$ level in Chinese cities was 61 $\mu g/m^3$ in 2015, three times as high as the global population-weighted mean (Zhang and Cao, 2015), with fewer than 1% of the Chinese cities met the air quality guidelines issued by the World Health Organization (Zhang and Crooks, 2012). Though estimates of the magnitude vary, fine particulates have been shown to have a significant impact on mortality and morbidity (GBD 2015). There are many recent papers establishing a causal link between pollution and health effects or mortality (c.f. Schlenker and Walker, 2015; Graff Zivin and Neidell, 2013), including papers focusing explicitly on mortality or morbidity in China (Chen et al., 2013). Pollution has also been shown to impact a variety of other outcomes, including school attendance (Currie et al., 2009), cognition (Bishop, Ketcham and Kuminoff, 2018), and early exposure has been tied to longer-run earnings (Isen, Rossin-Slater and Walker, 2017). Furthermore, there is a growing literature showing how individuals respond to pollution through defensive expenditures (Ito and Zhang, 2016; Deschenes, Greenstone and Shapiro, 2017; Sun, Kahn and Zheng, 2017). It is plausible that chronic pollution exposure could affect labor supply decisions, but most evidence to date focuses on productivity (e.g. Graff Zivin and Neidell, 2012; Chang et al., 2016*a*; Chang et al., 2016*b*; He, Liu and Salvo, 2016) or short-run impacts of pollution shocks on labor supply (e.g. Hanna and Oliva, 2015; Aragón, Miranda and Oliva, 2017). Despite the severity of the $PM_{2.5}$ levels and the large population that is affected, little is known regarding the effect of chronic $PM_{2.5}$ concentrations on labor supply. In this paper, we use restricted individual-level panel data from China, paired with remote-sensing pollution estimates, to estimate the impact of $PM_{2.5}$ on hours worked.

To estimate the impact of fine particulate matter on labor supply, a major challenge is controlling properly for confounding factors. For example, economic growth affects both pollution levels and labor demand. In this study, we take advantage of the panel structure of the data and estimate an individual fixed effects model to control for individual time-invariant characteristics, including heterogeneous responses to pollution. Unlike previous studies, we focus on longer-term exposure and use a representative survey with individuals from all segments of the population. We have restricted-access data, which allows us to flexibly control for macroeconomic conditions and factors such as regional differences in seasonality. Moreover, the restricted access data allow us to assign pollution concentrations to individuals with remote sensing estimates of pollution. This allows us to circumvent many of the measurement issues associated with using traditional ambient pollution monitoring data, particularly in China.

We contribute to the empirical research on the impact of $PM_{2.5}$ on labor supply in the several ways: first, we explore the impact of long term (annual) exposure to air pollution, which complements research that relies on short-run (weekly or daily) fluctuations of pollution; second, by using Chinese data, we are looking at a population exposed to a very high annual mean $PM_{2.5}$ level, the impact of which is unknown in the literature; third, our study is not limited to a specific industry or city/region, as we are using a nationally representative sample with both agricultural and non-agricultural workers; finally, we are able to match individuals to air pollution exposure at the sub-district level, the smallest census unit in China, which is a significant improvement in the accuracy of pollution assignment over existing studies using data from *in situ* pollution monitors with sparse coverage.

We find a large impact of particulate matter on hours worked. Our preferred fixed effects estimates show that a 1 $\mu g/m^3$ increase in $PM_{2.5}$ reduces the hours worked by 29 minutes per week for an average worker. Evaluated at the mean, this suggests that a one percent increase in annual average $PM_{2.5}$ concentrations decreases hours worked by about one percent. Extrapolating and ignoring general equilibrium considerations, if cities were to comply with China's new National Ambient Air Quality Standards (2012 NAAQS) hours worked by an average individual would increase by three and half hours per week.

The rest of the paper is organized as follows: section 2 provides background on air pollution and its regulation in China; section 3 and 4 present the data and empirical strategy, respectively; section 5 presents the findings; and section 6 concludes.

2 Fine Particulate Matter in China

Fine particulate matter, or $PM_{2.5}$, is an air pollutant that consists of tiny airborne particles less than 2.5 micrometers in aerodynamic diameter. In urban areas in China, the main sources of $PM_{2.5}$ are electric power plants, industrial facilities, automobiles, and heating, while in rural areas it is primarily due to biomass burning, agricultural dust and from windblown sources outside the region. According to official data, the annual mean $PM_{2.5}$ concentration across the 338 monitored cities was 50 $\mu g/m^3$ in 2016 (MEP, 2016), much higher than the 35 $\mu g/m^3$ standard set by 2012 NAAQS and the 10 $\mu g/m^3$ standard set by the World Health Organization (WHO, 2005). We note that rural areas in China contain very few *in situ* ambient air pollution monitors.

$PM_{2.5}$ has been shown to be an extremely harmful pollutant. Due to its size, it can penetrate the respiratory system and reach deep into the lungs and circulatory system. Its light weight also allows it to remain suspended in the air for prolonged periods. Because these particles are so small, conventional masks and air filters are not as effective in mitigating the impact of $PM_{2.5}$ on human health. A large literature finds that $PM_{2.5}$ causes and intensifies cardiovascular and respiratory diseases, especially in elderly, infants, and persons with existing health conditions, although others are susceptible to less serious health effects such as transient increases in respiratory symptoms, decreased lung function, or other physiologic changes (Dockery, 2001; Pope, 2000). Chronic exposure studies suggest relatively broad susceptibility to cumulative effects of long-term repeated exposure to fine particulate pollution, resulting in substantive estimates of population average loss of life expectancy in highly polluted environments (Pope, 2000).

Prior to 2012, there was no formal regulation of $PM_{2.5}$ in China. The 2012 National Ambient Air Quality Standard (NAAQS) started the monitoring and reporting of $PM_{2.5}$ and at the same time set stringent standards for other pollutants such as PM_{10}. The standard for the annual mean $PM_{2.5}$ is set at 35 $\mu g/m^3$ and the 24-hour mean at 75 $\mu g/m^3$, much higher than the WHO standards of 10 $\mu g/m^3$ and 25 $\mu g/m^3$ for the annual and 24-hour mean, respectively (WHO, 2005). The implementation of the new standards takes a staged approach, with the first phase implemented in 2012 covering 66 cities including municipalities, provincial capitals, provincial level cities, major cities in Jing-Jin-Ji region[1], Yangzi River Delta, and Pearl River Delta; the second phase implemented in 2013 covered 116 additional cities; and the third phase implemented in 2014 added another 177 cities. By the end of

[1] Also known as the national capital region comprising Beijing,Tianjin, and Hebei Province.

2014, all prefecture-level cities were regulated by 2012 NAAQS.[2]

As of 2017, there were 1,436 air pollution monitors across the country and the real-time air quality index was being published by China National Environmental Monitoring Center.[3] Figure 1 illustrates the spatial distribution of monitors in three Chinese cities. As shown in the figure, monitor coverage is sparse, even in densely populated cities.

3 Data

3.1 Labor supply

The main dataset we use is the restricted-use micro-data from the China Family Panel Studies (CFPS), which follows more than 33,000 adults in 635 sub-districts through the year 2010, 2012, and 2014 (Xie and Hu, 2014). The panel structure of the data allows us to partial out individual-specific time-invariant unobserved characteristics. The survey also provides rich information on individual, household, and community characteristics, as well as the sub-district in which each surveyed family resides.

Our main variable of interest is hours worked, which is reported at the individual level for each member of the surveyed household. We construct the average hours worked per week in the year prior to the interview. For agricultural labor hours, we use the average hours worked per week when an individual is involved in family agriculture; for non-agricultural labor hours, we use the number of hours worked across all current non-agricultural jobs. We do not include those who have both agricultural and non-agricultural jobs for two reasons:

[2] As a robustness check, we consider a 2SLS model leveraging the staged implementation of these standards in Section 5.3.

[3] Refer to http://www.cnemc.cn/sssj/ for more information.

first, it is difficult to accurately assign air pollution levels to such individuals given the lack of information on whether their agricultural and non-agricultural jobs are in the same location; second, due to the lack of information on the timing of family agriculture, we do not know whether an individual has jobs in both sectors concurrently or not, and it is not possible to determine the total hours worked for such individuals.

3.2 Air pollution

For air pollution, we use satellite-derived $PM_{2.5}$ estimates developed by van Donkelaar et al. (2016) that are produced by combining Aerosol Optical Depth (AOD) retrievals from the NASA MODIS, MISR, and SeaWIFS instruments with the GEOS-Chem chemical transport model, and subsequently calibrated to regional ground-based observations of both total and compositional mass using Geographically Weighted Regression (GWR).[4]

The data consist of estimated annual mean $PM_{2.5}$ concentrations from 2009 to 2014 at the global scale with a grid cell resolution of $0.01^{\circ} \times 0.01^{\circ}$, which corresponds to roughly a square kilometer. We aggregate these estimates at sub-districts level using location information provided by the 2010 Township Population Census.[5]

There has been an increase in number of studies in economics utilizing satellite-derived pollution estimates, especially in countries like China (Chen, Oliva and Zhang, 2017; Fu and Zhang, 2017; and Freeman et al., 2019). We use satellite-derived pollution estimates as an alternative to monitor data for several reasons. First of all, monitor level data, especially $PM_{2.5}$, is only partially available for our study period, although an extensive monitor network

[4] The calibration is done at the global scale and not for China exclusively. Monitoring $PM_{2.5}$ was not mandatory in China before 2012.

[5] There are a total of 42,403 sub-districts in the 2010 population census.

has been established post 2012. Second, there have been concerns regarding the validity of monitor data in China. Ghanem and Zhang (2014) find evidence of manipulation in 50% of the reported pollution levels that led to a discontinuity at the cut-off. Third, although real-time monitor reading could significantly reduce the potential manipulation through reporting, there have been cases of direct tampering of monitors in order to reduce reported pollution, by physically altering the monitor or by spraying water through the surrounding air to decrease concentrations locally (c.f. The Telegraph, Oct 26, 2016). Fourth, even with the recently established monitoring network, the pollution monitors are still sparsely distributed and rarely cover the rural areas. Figure 1 presents an example of the concentration of monitors in urban areas. The topmost panel shows the distribution of monitors in the city of Chongqing[6], one of China's biggest cities, where the 17 air pollution monitors are concentrated in the six central districts, leaving other 32 districts/counties without any monitor coverage. Using monitor data would require the assumption that the districts without monitors, mostly rural areas, have the same exposure level as the urban center located hundreds of miles away, which is highly implausible.[7]

3.3 Matching labor and pollution data

With access to restricted data from CFPS, we are able to match air pollution to individuals at the sub-district level, the smallest unit of census block in China. Using survey year and

[6] According to Chongqing Municipal Government, the city has a population of more than 30 million and an area of 82,400 square kilometer. The other two panels in the figure illustrate monitor distribution in Beijing and Shanghai, with a population of 21.54 million and 26.32 million and an area of 16,808, and 6,340 km^2, respectively.

[7] Figure A.1 in the Appendix presents the distribution and large variation of annual mean $PM_{2.5}$ across sub-districts in Chongqing in 2014, with a minimum of 22 $\mu g/m^3$ and a maximum of 61 $\mu g/m^3$. In addition to concerns about sparse coverage, we also note that there could be concerns about endogenous monitor siting(Grainger, Schreiber and Chang, 2018).

month information[8], we calculate the weighted average of pollution 12 month prior to the interview. For an individual living in sub-district j interviewed in year t and month m, the pollution level assigned is

$$Pollution_{jtm} = Pollution_{jt} * m/12 + Pollution_{j(t-1)} * (12 - m)/12.$$

We assume a person works and lives in the same sub-districts. To the extent that a worker may commute to nearby sub-districts, we do not expect their pollution exposure to differ significantly due to the high spatial correlation of pollution estimates. It is of course possible that individuals may commute longer distances, but it is unlikely that these commuting patterns are somehow systematic so as to cause bias in our estimates.

3.4 Descriptive statistics

In the baseline analysis of the effect of $PM_{2.5}$ on hours worked, we include only the individuals between 16 and 75 years of age who are interviewed in at least two of the three surveys and have no missing information in interview timing, person-specific identifier, sub-district identifier, hours worked, or key demographic characteristics.[9] We do not include the post-migration observations of individuals who have moved across sub-districts. Due to the lack of information on the timing of the move, we are unable to assign the pollution exposure accurately to these observations. The resulting sample size for our baseline analysis is 25,472

[8]Table A.1 in Appendix presents the survey schedule and the number of individuals surveyed in each month.

[9]Interview timing includes interview month and year. Key demographic characteristics include age, gender, education, marital status, whether the person has a dependent younger than 7 years of age or older than 75 years of year, self-rated health, and whether the person works in agricultural or non-agricultural sector.

observations for 11,388 individuals.

Table 1 Panel A displays the sample statistics including hours worked, annual mean $PM_{2.5}$, and key demographic characteristics for the full sample as well as those who work in agriculture and non-agricultural sector separately.

The average hours worked per week is 42.5, and those in non-agricultural sectors work almost 20 hours longer than those employed only in agriculture. Figures 2 and 3 show the distribution of hours worked and the within-person changes in the hours worked respectively. As shown in Figure 3, the distribution of the within-person changes in hours worked is centered around zero, with a standard deviation of 23.85 as reported in Table 1 Panel B column (1).

The average annual $PM_{2.5}$ for the sample is 44 $\mu g/m^3$. Non-agricultural workers face higher pollution with a $PM_{2.5}$ level of 49 $\mu g/m^3$ compared to 42 $\mu g/m^3$ for those who work in agriculture. Figure 4 presents the distribution of $PM_{2.5}$ and the within-person changes in $PM_{2.5}$ with a mean of zero and a standard deviation of 5.12 as shown in Table 1 Panel B. Table 2 reports the inter-quartile range of $PM_{2.5}$.

4 Empirical strategy

Given the panel data from the CFPS and remote sensing estimates of air pollution at the sub-district level, we are interested in the impact of $PM_{2.5}$ on hours worked. Specifically, we estimate a regression of the following form in the baseline model:

$$Hours_{ijcptm} = \beta Pollution_{jt} + \gamma X_{ijcptm} + \alpha_i + \lambda_{pm} + \delta_{ct} + \epsilon_{ijcptm} \tag{1}$$

where $Hours_{ijcptm}$ is the average hours worked per week for an individual i located in sub-district j county c province p interviewed in month m year t; $Pollution_{jt}$ is the mean pollution level in sub-district j year t; X_{ijcptm} represents time-variant individual characteristics and α_i represents time-invariant individual characteristics; λ_{pm} is the province-by-month fixed effects; δ_{ct} is the county by survey-year fixed effect; and ϵ_{ijcptm} represents all other unobserved determinants for labor supply.

Estimating the impact of air pollution on hours worked has several challenges. First, individuals have heterogeneous responses to air pollution. For example, workers with varied health conditions are likely to be affected differently; those who are more concerned about air pollution are likely to respond more through avoidance behavior; individuals with flexible work hours would respond differently from those with fixed work hours. To this effect, we focus on within-person differences in the exposure to air pollution by using an individual fixed effects model. Second, there are unobserved factors that affect both air pollution and the outcome variables, especially macro-economic conditions such as recession and structural changes in the economy. To control for such unobserved factors, we include county-by-year fixed effects to flexibly control for common county-level shocks. Third, seasonal variations could also cause spurious correlation between labor supply and air pollution, especially for sectors that are sensitive to climate and weather events, such as agriculture and construction. As counties with close geographical proximity are likely to share similar climate, we include province-by-month fixed effects to account for seasonality that can vary by region.

5 Results

5.1 $PM_{2.5}$ and labor force participation and unemployment

Before we estimate the main effect of $PM_{2.5}$ on hours worked, we first formally test for response on the extensive margin i.e. the effect of $PM_{2.5}$ concentrations on labor force participation and unemployment. Using whether an individual is in the labor force and whether an individual is employed as outcome variables, we estimate equation (1).[10]

The results in Table 3 show that $PM_{2.5}$ has no significant effect on labor force participation (column (1)) or unemployment (column (2)), and magnitude of the point estimates are economically small. The sign of the point estimates could indicate that an increase in $PM_{2.5}$ is linked to increased economic activities, therefore results in higher labor force participation and lower unemployment.

After controlling for major economic shocks using county-by-year fixed effect and capturing both time-invariant and time-variant individual characteristics, we do not find evidence of an effect of annual $PM_{2.5}$ concentrations on labor supply on the extensive margin.

5.2 $PM_{2.5}$ and hours worked

Table 4 shows the estimates of equation (1) with hours worked as the outcome variable. The baseline regression result in Table 4 column (4) shows that with a 1 $\mu g/m^3$ increase in $PM_{2.5}$,

[10]The sample restrictions for the labor force participation and unemployment models are the same as the baseline model for hours worked except for the restriction on non-missing value for dependent variable, which is model specific. Among the 49,624 observation in the labor force participation model, 44% are not in the labor force. Among the 27,924 observations in the unemployment model, about 9% are unemployed or did not report hours worked.

hours worked decrease by 0.48 hours per week and this estimate is significant at 5% level.[11] The estimates do not change significantly with the inclusion of extreme values (column (5)).

These effects are large and suggest that changes in air pollution have a large effect on a person's labor supply choices. The average $PM_{2.5}$ in our sample is roughly 44 $\mu g/m^3$, and the average number of hours worked in the sample is about 42 hours, so in percentage terms this corresponds to an elasticity of nearly negative one.

We expect that there could be heterogeneity in the effect of pollution on hours worked, so we test this in several ways. First, Figure 5 shows the effect of $PM_{2.5}$ by quartile of $PM_{2.5}$. Second, the effect of $PM_{2.5}$ on hours worked may vary by individual characteristics. To test for heterogeneous effects, we interact $PM_{2.5}$ with indicator variables for male, lower than primary school education, having dependent, bad health, and agricultural sector as well as for age below 35, between 35 and 55, or above 55. Figure 6 presents the heterogeneous effect of $PM_{2.5}$ on hours worked. We do not observe significant differences of the effect across demographic categories, though we note that these tests have low power and we have not adjusted standard errors for multiple hypothesis testing.[12]

5.3 Robustness checks

In our baseline model, we included county-by-year fixed effects to account for the common factors that may affect air pollution and labor hours at the same time. However, there are

[11] The estimates with alternative specifications (including natural logs) are shown in Table A.2 in the Appendix.

[12] We note, though, that contrary to Aragón, Miranda and Oliva (2017), our estimates show no significant difference in the impact of $PM_{2.5}$ on the individuals with dependents, whose health may be affected by air pollution. This may be due to differences in family structure in China compared to in Latin America. In China, caretaking of dependents is more commonly done by the child's grandparents, who are out of the workforce.

concerns that some factors may affect air quality in a smaller geographical area. For example, traffic regulations in a county may affect the ambient air quality in areas with heavy traffic, while reduced emissions from a factory may affect the surrounding area. However both measures could have implications for labor supply. If this is the case, our estimates may suffer from attenuation bias. It is worth noting that such pollution reduction measures are likely to affect more than just the regulated area and the spill-over effects are likely to be stronger within a county due to close geographical proximity.

Some studies, such as Chang et al. (2016*b*) and Fu and Zhang (2017), have raised concern on reverse causality of economic outcomes on pollution exposure. We do not consider reverse causality a serious threat in our study as an increase in hours worked by an individual is less likely to cause drastic changes in ambient air quality, although we acknowledge the potential general equilibrium effect when the population as a whole, especially those in pollution generating sectors, increase their working hours, the pollution level will also likely go up. In our data, less than 25% of the sample works in heavy polluting industries such as mining, manufacturing, electricity production, construction and transportation. If increase in hours worked by these workers resulted in increased pollution, our estimates are likely to be biased upwards.

There is also measurement error in satellite-derived pollution estimates, and for fine particulates ground level pollution tends to be under-predicted by remote sensing on extremely polluted days. However, the issue is more severe for short-term estimates, such as hourly or daily, and is less prominent when we use the annual mean pollution estimates. Unlike studies that uses monitor based pollution data, the "Berkson" error, which happens when a group average exposure level is assigned to individuals with certain same characteristics, is smaller in our study. However, we still face the issue that the exposure level measured at residence could be different from that at work place.

The previous literature has addressed some of the above concerns of endogeneity using an instrumental variables approach. In this section, we use the 2012 NAAQS as an instrument[13] to obtain plausibly-exogenous variation in $PM_{2.5}$ concentrations. The 2012 NAAQS, aimed at reducing ambient air pollution, was implemented in three stages (described in detail in Section 2.2) and is likely to lead to differentiated timing in the pollution reduction across cities.[14]

We estimate the following two-stage least squares (2SLS) model:

$$Pollution_{ijcptm} = \pi_1 NAAQS_{ct} + \gamma_1 X_{ijcptm} + \alpha_{1i} + \lambda_{1pm} + \delta_{1pt} + \epsilon_{1ijcptm} \tag{2}$$

$$Hours_{ijcptm} = \pi_2 \hat{Pollution}_{ijctm} + \gamma_2 X_{ijcptm} + \alpha_{2i} + \lambda_{2pm} + \delta_{2pt} + \epsilon_{2ijcptm} \tag{3}$$

where in the first-stage (equation (2)), we estimate the $PM_{2.5}$ levels facing an individual i living in province p, county c, sub-district j, in year t, and month m as a function of whether the NAAQS has been implemented in county c year t. We control for individual fixed effects, province by interview month fixed effects, and covariates. As the policy varies by county and year, we are unable to include county-by-year fixed effects in this model, therefore we include province-by-year fixed effects to flexibly control for macroeconomic shocks at the province

[13]The authors are aware of alternative instruments such as thermal inversion(Fu and Zhang, 2017; Chen, Oliva and Zhang, 2017). However, due to the limited access to the restricted version fo CFPS data, we are unable to the merge these instruments with our dataset.

[14]We do not expect the policy to have any direct impact on the hours worked in the short run as the performance evaluation for government officials still places significant weight on economic growth. Therefore, it is unlikely that cities will take radical measures immediately to reduce emissions risking economic slow down. It is also unlikely that industries will relocate to areas with less stringent pollution regulation as the difference in regulations is temporary due to the short 3-year roll-out of the 2012 NAAQS.

level. In the second-stage (equation (3)), we estimate the effect of the predicted pollution exposure on hours worked.

Table 5 column (2) panel B presents the first stage estimate of our preferred specification (equation(6)) and it shows that the implementation of NAAQS 2012 led to a reduction of $PM_{2.5}$ by about 0.99 $\mu g/m^3$. Though the effect size is small, it is statistically significant. The F-statistics testing for weak instrument test indicate a strong first stage.

The second stage of the 2SLS model shows that a 1 $\mu g/m^3$ reduction in $PM_{2.5}$ leads to an increase of hours worked by 1.6 hours, as shown in Table 5 column (2) panel A and the effect size is much larger than the fixed effects estimate. The alternative 2SLS specification including only year effects are shown in Table 5 column (4), where a one unit increase in annual $PM_{2.5}$ leads to a decrease in hours worked by 1.24 hours per week. Fixed effects models are presented in Table 5 as the estimates from 2SLS models are not directly comparable with our baseline results in Table 4 due to the change in the level of fixed effects included to control macroeconomic shocks. Table 5 column (1) presents the fixed effects model estimates with province-by-year fixed effects while column (3) presents the estimates from fixed effects model with year fixed effects.

6 Conclusion

Although the exposure to $PM_{2.5}$ is very high in developing countries like China, very little is known on how the long-term exposure to such high level of $PM_{2.5}$ affects labor supply. The use of remote sensing pollution estimates enables us to use more reliable $PM_{2.5}$ estimates at a finer scale and greater geographical coverage, while the restricted individual-level panel data from CFPS allows us to match individual to exposure level by sub-districts. Our study expands beyond a single urban area with limited coverage of pollution monitors or a single farm/factory. A recent paper by Aragón, Miranda and Oliva (2017) shows that short-term exposure to $PM_{2.5}$ affects hours worked only for the households with susceptible individuals. They find that a 1 $\mu g/m^3$ increase in $PM_{2.5}$ decreases the hours worked by 12 minutes (0.19 hour), and if $PM_{2.5}$ exceeds 35 $\mu g/m^3$, the hours worked reduce by 6.8 hours. In our study, the annual mean $PM_{2.5}$ concentration *at the national level* is similar to the weekly mean in Lima as in Aragón, Miranda and Oliva (2017), with more than 70% of the sample facing $PM_{2.5}$ level higher than 35 $\mu g/m^3$ and the mean $PM_{2.5}$ around 45 $\mu g/m^3$. We find that the long-term exposure has a significant impact on hours worked. In our fixed effects specification, we estimate that a 1 $\mu g/m^3$ increase in $PM_{2.5}$ can lead to a reduction of labor hours by 29 minutes (0.48 hours) per week.

There are several caveats worth noting. First, we observe an individual's home address and assign pollution levels accordingly. For workers who commute long distances to work, this assignment could introduce substantial measurement error. If differences between pollution at the residence and workplace is not somehow systematic, the measurement error would be classical, but the data do not allow us to test this. Second, our measurement of pollution using remote sensing is likely an underestimate, as saturation is generally observed in the estimates for higher pollution levels. We note that our instrumental variables estimates are roughly twice as large as our baseline fixed effects estimates, which is consistent with this type of measurement error. Third, an individual could respond to higher pollution levels by sorting to a location with lower pollution levels. In Appendix B we discuss this possibility in the context of our data. Finally, as our measure of hours worked is self-reported, there could be concerns about recall bias. As discussed in Appendix C, we note that measurement error in our dependent variable is not likely correlated with other explanatory variables and is unlikely to cause bias in the estimation.

The economy wide impact of a reduction in ambient pollution could be substantial, though extrapolating would require strong assumptions. According to the 2010 Population Census, China has a working population of 715 million. If we take the estimate of 29 minutes from our fixed effects model, a 1 $\mu g/m^3$ reduction in $PM_{2.5}$ can lead to 24[15] more hours worked per person per year and more than 17 billion more hours supplied economy-wide. Further, by complying with China's new NAAQS for annual mean $PM_{2.5}$ of 35 $\mu g/m^3$, we would observe the labor hours to increase by three and half hours per worker per week and potentially an economy-wide increase of 125 billion hours in labor supply per year. In addition to affecting labor hours directly, over the longer run one would expect changes in $PM_{2.5}$ levels to also have general equilibrium impacts that would in turn affect labor supply. For example, a change in the pollution levels may result in residential sorting, although not shown in our data set, that has been documented elsewhere in the literature. It may also affect occupational choices, which may, in turn, affect hours worked. These effects on labor hours are not taken into account in this paper and will require careful attention in future research.

Our estimates contribute to the empirical literature that evaluates the effect of $PM_{2.5}$ on human capital and labor supply and have important policy implications for developing countries with extremely high annual average concentrations. While a few recent studies find short-run impacts of pollution on labor supply, we find that the impact of chronic exposure is

[15] Assuming 50 working weeks in a year.

large and significant. The results suggest that researchers and policymakers should consider not only productivity impacts, but also labor supply impacts, when considering policies to decrease average concentrations of pollution.

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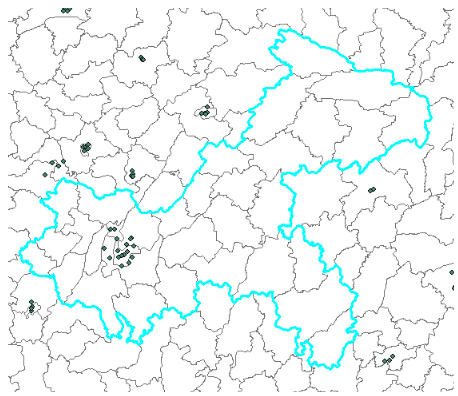
Figure 1: Ambient air pollution monitors in three cities



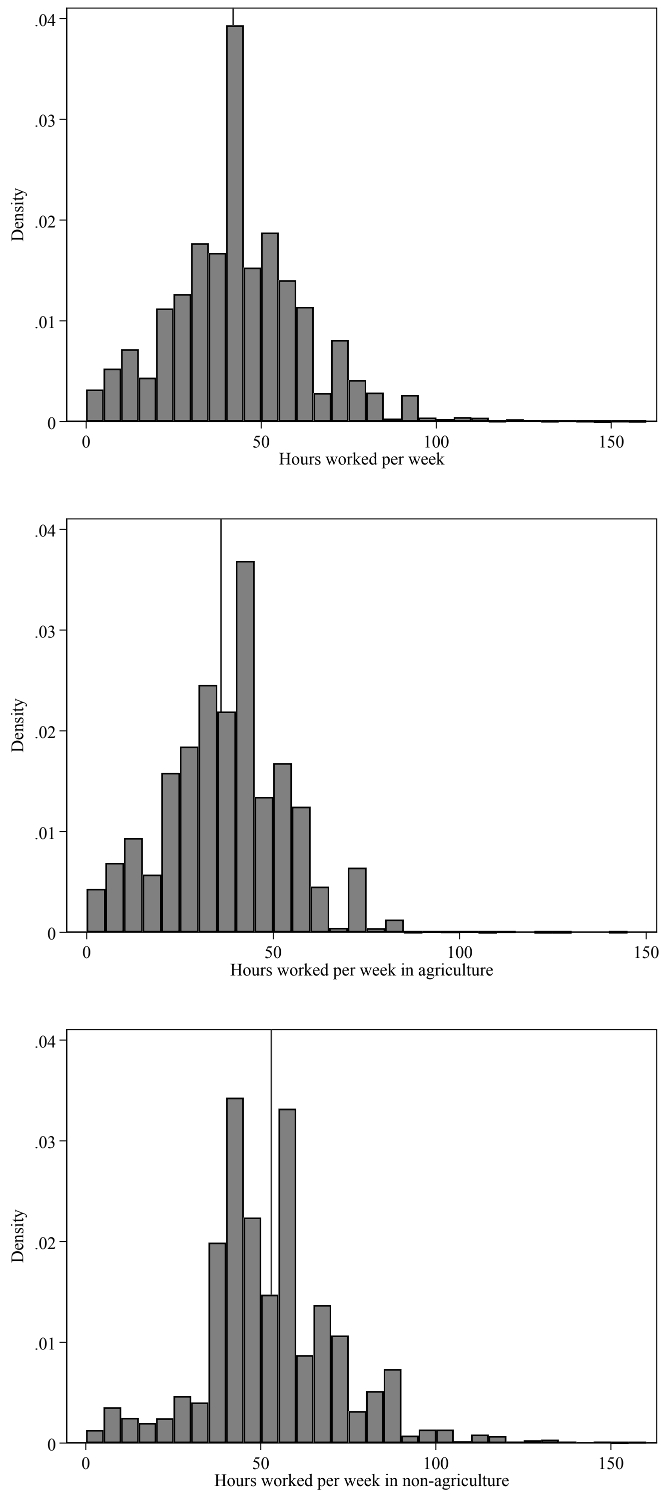
Chongqing

Beijing

Shanghai

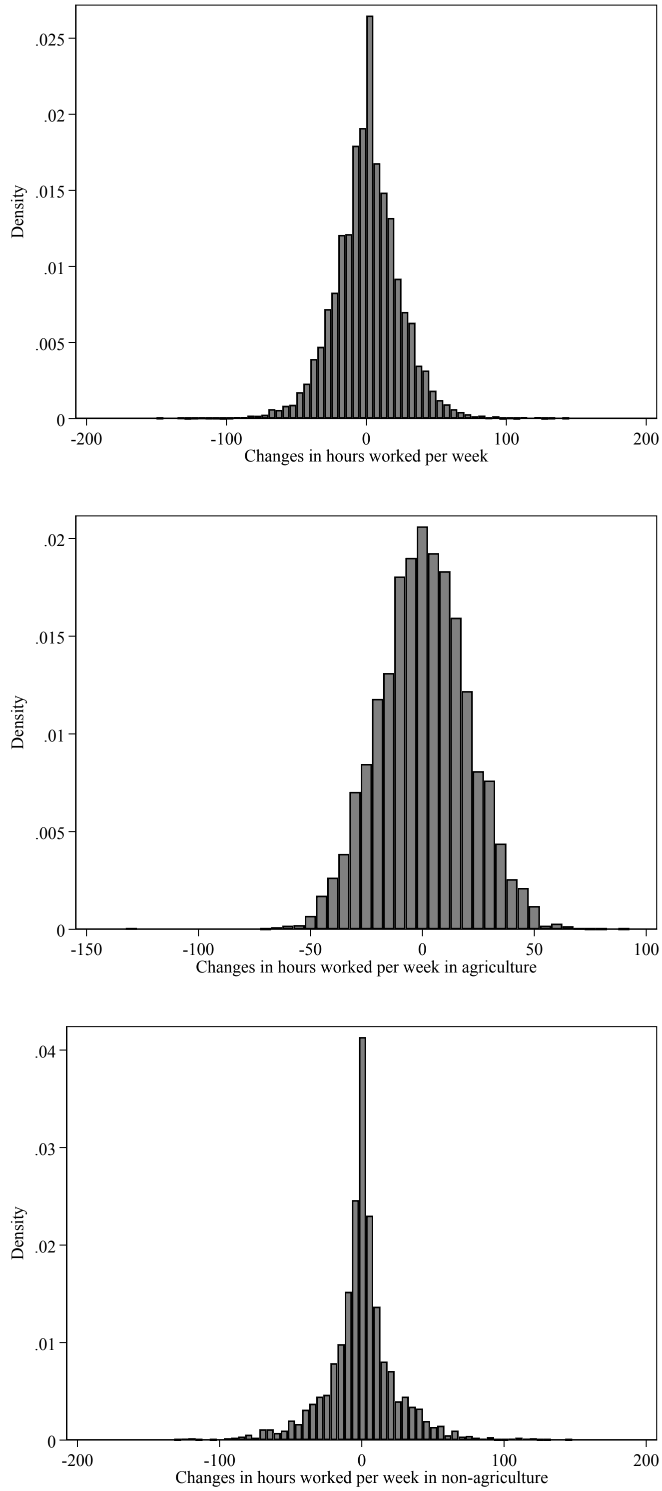
Notes: The three maps show the spatial distribution of Chongqing, Beijing and Shanghai. Each dot represents a $PM_{2.5}$ monitor's location in the year 2017. Maps are not of the same scale; the cities are 82,400, 16,808, and 6,340 km^2, respectively.

Figure 2: Distribution of hours worked



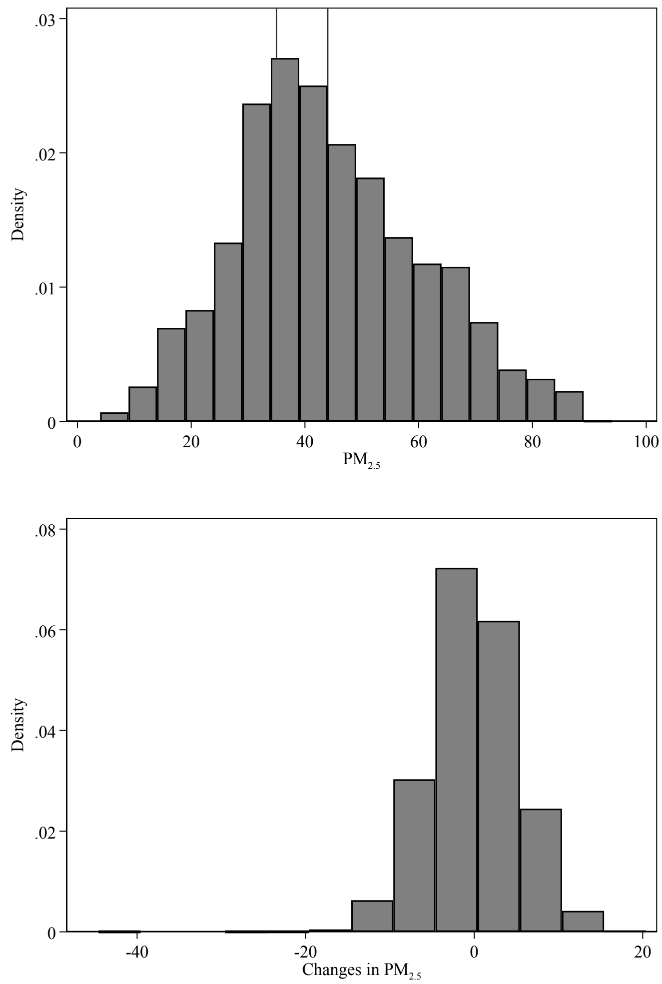
Note: The graphs show the distribution of hours worked, hours worked in agriculture and non-agriculture respectively. The vertical lines represent the mean hours worked per week (42 hours), mean hours worked per week in agriculture (36 hours) and non-agriculture (53 hours).

Figure 3: Distribution of changes in hours worked



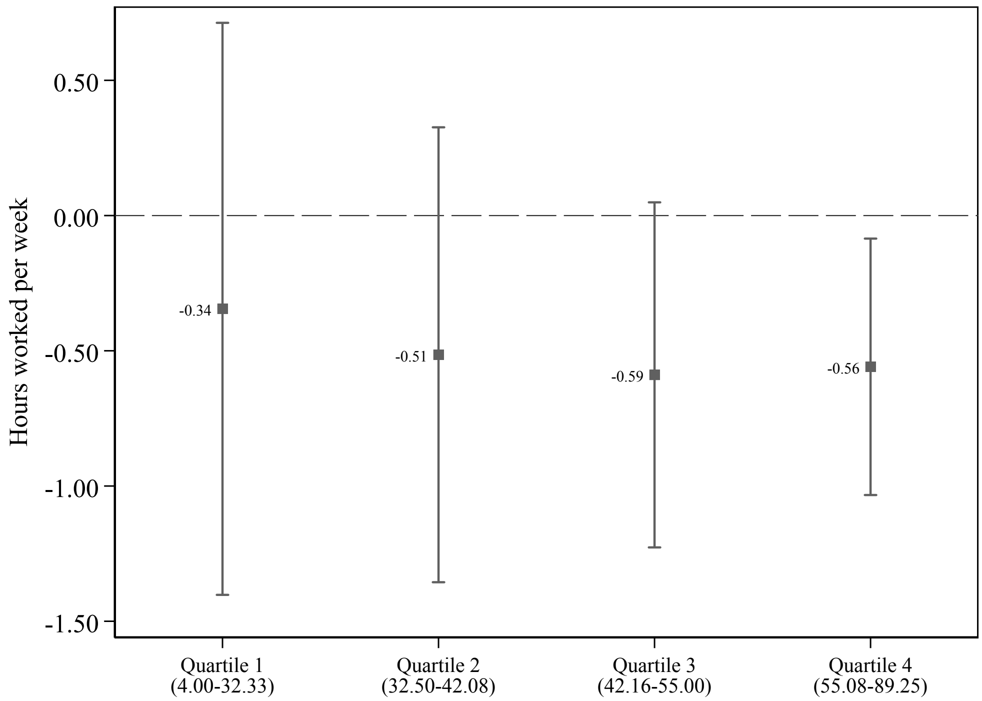
Note: The graphs show the distribution of the within-person changes in hours worked, hours worked in agriculture and hours worked in non-agriculture respectively.

Figure 4: Distribution of $PM_{2.5}$ and changes in $PM_{2.5}$



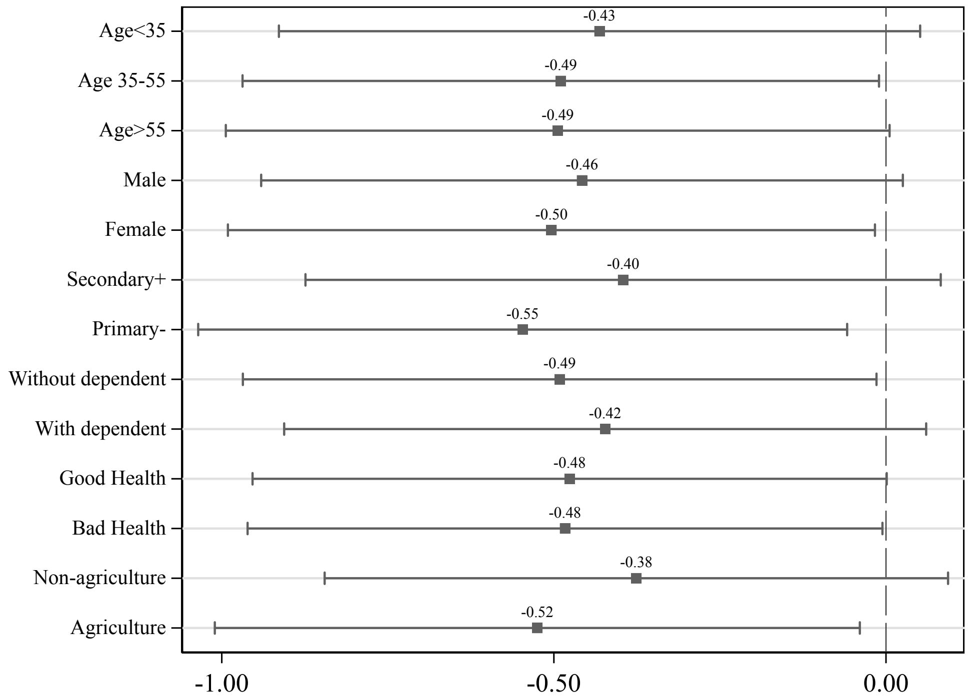
Note: The upper graph shows the distribution of $PM_{2.5}$. The two vertical lines, from left to right, represent China's new air pollution standard for the annual mean of $PM_{2.5}$ (35 $\mu g/m^3$) and the mean $PM_{2.5}$ exposure of the sample (42 $\mu g/m^3$). The lower graph shows the distribution of within-person changes in $PM_{2.5}$

Figure 5: Non-linearity of the effect of $PM_{2.5}$



Note: The graph shows the non-linearity of the effect of $PM_{2.5}$ on hours worked per week by estimating a model with interactions between a continuous variable of $PM_{2.5}$ and binary variables indicating which quartile the initial $PM_{2.5}$ an individual faces belong to. The squares on the graph present the point estimates while the bars show 95% confidence intervals. The horizontal dash line indicates an effect size of zero. The numbers in brackets show the range of $PM_{2.5}$ in $\mu g/m^3$ for each quartile. The model include individual fixed effects, county-by-year fixed effects, interview month fixed effects and time-varying individual controls such as education, marital status, whether the individual has dependents, whether the individual has more than one job and whether the individual works in agricultural or non-agricultural sector.

Figure 6: Heterogeneous effect on hours worked



Note: The graph shows the heterogeneous effect of $PM_{2.5}$ on hours worked per week estimated using models with interactions between $PM_{2.5}$ and individual characteristics. The squares on the graph present the point estimates while the bars show 95% confidence intervals. The vertical dash line indicates an effect size of zero. All the models include individual fixed effects, county-by-year fixed effects, interview month fixed effects and time-varying individual controls such as education, marital status, whether the individual has dependents, whether the individual has more than one job and whether the individual works in agricultural or non-agricultural sector. Age and age square are included in all models except the model evaluating the effect by age category, for which we include age category instead.

Table 1: Descriptive statistics

	(1) All	(2) Agriculture	(3) Non-agriculture
Panel A: Sample statistics			
Hours worked per week	42.54	35.87	54.73
	(20.27)	(16.06)	(21.47)
$PM_{2.5}$	44.26	41.91	48.57
	(16.33)	(16.54)	(15.02)
Age	45.90	49.15	39.97
	(12.31)	(11.88)	(10.76)
Gender: male=1	0.50	0.44	0.62
	(0.50)	(0.50)	(0.49)
Education: below primary=1	0.56	0.73	0.25
	(0.50)	(0.44)	(0.44)
Marital status: single=1	0.09	0.07	0.13
	(0.29)	(0.26)	(0.34)
Dependent: yes=1	0.16	0.13	0.21
	(0.36)	(0.33)	(0.41)
Observations	25472	16468	9004
Panel B: Within-person variations			
Changes in hours worked	-0.08	-1.62	3.20
	(23.85)	(21.81)	(27.40)
Changes in $PM_{2.5}$	-0.07	-0.26	0.28
	(5.12)	(4.89)	(5.52)

Note: Panel A of this table provides the sample statistics for the key variables for the full sample (column 1), those who work in family agriculture (column 2) and those who work in non-agricultural section (column 3). The standard deviations are provided in parentheses and the sample size at the bottom of the panel. Panel B of this table provides the within-person variations in hours worked and $PM_{2.5}$.

Table 2: Inter-quartile range of $PM_{2.5}$

	(1) Lower bound	(2) Upper bound
Quartile 1	4.00	32.33
Quartile 2	32.50	42.08
Quartile 3	42.16	55.00
Quartile 4	55.08	89.25

Note: The table presents the inter-quartile range of $PM_{2.5}$.

Table 3: Impact of air pollution on labor force participation and unemployment

	(1) Labor Force Participation	(2) Unemployment
$PM_{2.5}$	0.007	-0.002
	(0.004)	(0.004)
Individual fixed effects	Yes	Yes
Province by interview month fixed effects	Yes	Yes
City by year fixed effects	Yes	Yes
N	49624	27924

Notes: The table presents estimates for the impact of $PM_{2.5}$ on labor force participation (column 1) and unemployment (column 2). All the models include individual fixed effects, county-by-year fixed effects, province-month fixed effects and time-varying individual controls such as age, age squared, education, marital status, whether the individual has dependents, whether the individual has more than one job and whether the individual works in agricultural or non-agricultural sector. The standard errors shown in parentheses are clustered at county level. Statistical significance is denoted by * for $p < 0.1$, ** for $p < 0.05$, *** for $p < 0.01$.

Table 4: Impact of air pollution on hours worked: fixed effects model

	(1)	(2)	(3)	(4)	(5)
$PM_{2.5}$	0.153*	0.043	-0.418*	-0.486**	-0.433*
	(0.083)	(0.094)	(0.216)	(0.242)	(0.234)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes
Province-by-month fixed effects		Yes		Yes	Yes
County-by-year fixed effects			Yes	Yes	Yes
N	25472	25472	25472	25472	25161

Notes: The table presents estimates for the impact of $PM_{2.5}$ on hours worked per week. Column 1 to 3 shows the estimate from the model with individual fixed effects, individual and county-by-year fixed effects, and individual and province-month fixed effects, respectively. Column 4 is our preferred baseline model. Column 5 shows the estimate with the inclusion of those with extreme values of the hours worked. All the models include time-varying individual controls such as age, age squared, education, marital status, whether the individual has dependents, whether the individual has more than one job and whether the individual works in agricultural or non-agricultural sector. The standard errors shown in parentheses are clustered at county level. Statistical significance is denoted by * for $p < 0.1$, ** for $p < 0.05$, *** for $p < 0.01$.

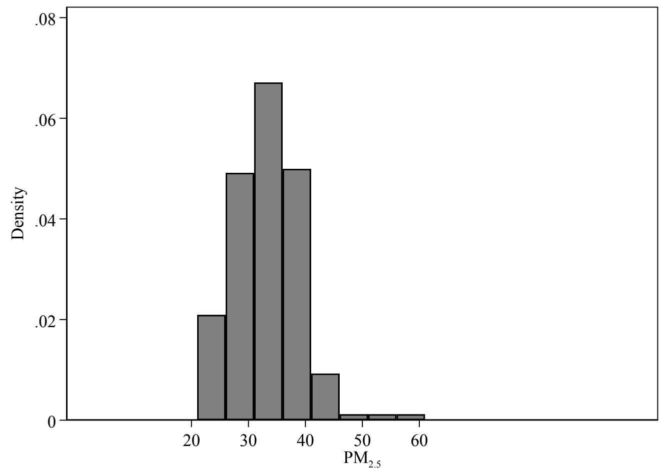
Table 5: Impact of $PM_{2.5}$ on hours worked: 2SLS

	(1) 2SLS	(2) FE	(3) 2SLS	(4) FE
Panel A: Second Stage				
$PM_{2.5}$	-0.229***	-1.601**	-0.341***	-1.243***
	(0.071)	(0.716)	(0.058)	(0.457)
Kleibergen-Paap F statistics		121.06		166.70
Panel B: First Stage				
Instrument		-0.987***		-1.157***
		(0.090)		(0.090)
Individual fixed effects	Yes	Yes	Yes	Yes
Province-by-month fixed effects	Yes	Yes	Yes	Yes
Province-by-year fixed effects	Yes	Yes	No	No
County fixed effects	No	No	Yes	Yes
Year fixed effects	No	No	Yes	Yes
N	25472	25472	25472	25472

Note: The table provides the estimates of the effect of $PM_{2.5}$ on hours worked from the 2SLS models and their corresponding fixed effects models. Column 1 and 2 provide the estimates from 2SLS model and FE model with province by year fixed effects, respectively while column 3 and 4 present the estimates from the models with year fixed effects. All the models include individual fixed effects, province-month fixed effects and time-varying individual controls such as age, age squared, education, marital status, whether the individual has dependents, whether the individual has more than one job and whether the individual works in agricultural or non-agricultural sector. The standard errors shown in parentheses are clustered at individual-level. Statistical significance is denoted by * for $p < 0.1$, ** for $p < 0.05$, *** for $p < 0.01$.

A Additional figures and tables

Figure A.1: Distribution of 2014 annual mean $PM_{2.5}$ in Chongqing



Note: The graph shows the distribution of 2014 annual mean $PM_{2.5}$ across all sub-districts in Chongqing.

Table A.1: Interview year and month

	Year of interview						
Month	2010	2011	2012	2013	2014	2015	Total
Jan	0	95	0	18	0	249	362
Feb	0	6	0	60	0	13	79
Mar	0	45	0	13	0	32	90
Apr	380	0	0	0	0	2	382
May	1,352	0	0	0	0	18	1,370
Jun	1,586	0	0	0	0	3	1,589
Jul	2,407	0	1,293	0	2,968	0	6,668
Aug	2,442	0	4,618	0	3,505	0	10,565
Sep	90	7	1,116	0	570	0	1,783
Oct	29	0	42	0	528	0	599
Nov	35	0	31	0	250	0	316
Dec	115	0	1,412	0	142	0	1,669
Total	8,436	153	8,512	91	7,963	317	25,472

Note: The table presents the number of interviews conducted by interview year and month.

Table A.2: Impact of air pollution on hours worked: alternative specifications

	(1) Hours	(2) Log Hours	(3) Log Hours
Log $PM_{2.5}$	-21.206*		-0.698*
	(12.311)		(0.391)
$PM_{2.5}$		-0.018*	
		(0.009)	
Individual fixed effects	Yes	Yes	Yes
Province-by-onth fixed effects	Yes	Yes	Yes
County-by-year fixed effects	Yes	Yes	Yes
N	25472	25472	25472

Note: The table presents the estimates from alternative specifications used in evaluating the impact of $PM_{2.5}$ on hours worked. Column 1 uses the log-linear specification and estimates the effect of 1% increase in $PM_{2.5}$ on hours worked. Column 2 used the linear-log specification and estimates the effect of 1 $\mu g/m^3$ increase of $PM_{2.5}$ on the hours worked in percentage terms. Column 3 uses the log-log specification and estimates the effect of 1% increase in $PM_{2.5}$ on the hours worked in percentage terms. All the models include individual fixed effects, county-by-year fixed effects, province-month fixed effects and time-varying individual controls such as age, age squared, education, marital status, whether the individual has dependents, whether the individual has more than one job and whether the individual works in agricultural or non-agricultural sector. The standard errors shown in parentheses are clustered at county level. Statistical significance is denoted by * for $p < 0.1$, ** for $p < 0.05$, *** for $p < 0.01$.

B Sorting

Residential sorting could also be a concern, as individuals with similar unobserved characteristics might re-locate in the same manner according to the pollution levels. Although the survey tracks individuals as they move, the observations for the survey immediately after moving were removed from the sample, as information on the exact timing of move is not available, making an accurate assignment of pollution exposure impossible. However, we do know the pollution exposure for the year prior to the interview at the new interview location, which means we could compare the pollution levels of the sub-districts these individuals moved from to the ones they moved to. We find that among the total 197 movers, 167 moved to areas with higher $PM_{2.5}$ and only 29 moved to areas with lower $PM_{2.5}$. A summary of the individual characteristics of the movers is presented in Table B.1. As compared to those who moved to areas with higher pollution, those who moved to sub-districts with lower pollution have higher education and more dependents; however due to the small sample size[16], these differences are not statistically significant.

For air pollution led migration to happen, we would expect those who move to have a higher environmental awareness. In the survey, individuals were asked to rate the severity of pollution in China from 0 to 10 and the average rating is 6 in our sample. The average rating by the movers is 6.4, which is not statistically different from the sample mean. In addition, those who moved to more polluted cities gave an average rating of 6.45 and those who moved to less polluted cities averaged at 6. Though the sample size for migrant is very small, we do not observe any difference in environmental awareness in this group and it is less likely that such a group is moving due to pollution concerns.

We also follow the attrition test for fixed effects models suggested by Wooldridge (2010, chapter 19.9.2) to formally test whether $PM_{2.5}$ has led to residential sorting. We create an indicator variable for individuals who moved before they drop out of the sample and add the indicator variable as a control in the baseline model. Table C.1 column (3) shows that the indicator variable is not statistically significant, suggesting that attrition bias may not be a concern. This result is in contradiction to the study by Chen, Oliva and Zhang (2017), in which air pollution is found to be responsible for large changes in inflows and outflows of migration in China. However, this may be because their study investigates the effect of an increasing pollution level at five-year intervals, as migration is likely to respond to air pollution slowly due to the costly and non-reversible nature of the decision.

[16] The total number of movers is very small in our sample (less than 1% of the individuals) and this is partially due to the large amount of missing covariates in the data. Without restricting the sample, we have about 6% of movers, out of which about 75% moved to areas with higher pollution and 25% moved to areas with lower pollution.

Table B.1: Mover Characteristics

	(1) All movers	(2) Increased pollution	(3) Reduced pollution
Age	39.12	39.56	36.59
	(10.80)	(11.15)	(8.52)
Gender: male=1	0.52	0.53	0.48
	(0.50)	(0.50)	(0.51)
Education: below primary=1	0.28	0.30	0.21
	(0.45)	(0.46)	(0.41)
Marital status: single=1	0.15	0.15	0.14
	(0.36)	(0.36)	(0.35)
dp	0.19	0.19	0.24
	(0.40)	(0.39)	(0.44)
Agricultural sector	0.30	0.31	0.24
	(0.46)	(0.46)	(0.44)
Observations	197	167	29

Note: This table provides the statistics for mover characteristics. Column 1 summarizes the characteristics for all moves while column 2 and 3 summarize the characteristics for movers who moved to sub-districts with higher and lower $PM_{2.5}$ respectively. The standard deviations are provided in parentheses and number of moves at the bottom of the table.

Table B.2: Attrition Bias

	(1) Attrition Bias
$PM_{2.5}$	-0.480**
	(0.242)
Moved in the next wave	0.860
	(1.825)
Individual fixed effects	Yes
Province by interview month fixed effects	Yes
City by year fixed effects	Yes
N	25472

Note: The table presents the estimates from attrition bias test by including the indicator variable of moved in the next wave. It includes individual fixed effects, county-year fixed effects, province-month fixed effects and time-varying individual controls such as age, age squared, education, marital status, whether the individual has dependents, whether the individual has more than one job and whether the individual works in agricultural or non-agricultural sector. The standard errors shown in parentheses are clustered at county level. Statistical significance is denoted by * for $p < 0.1$, ** for $p < 0.05$, *** for $p < 0.01$.

C Recall bias in hours worked

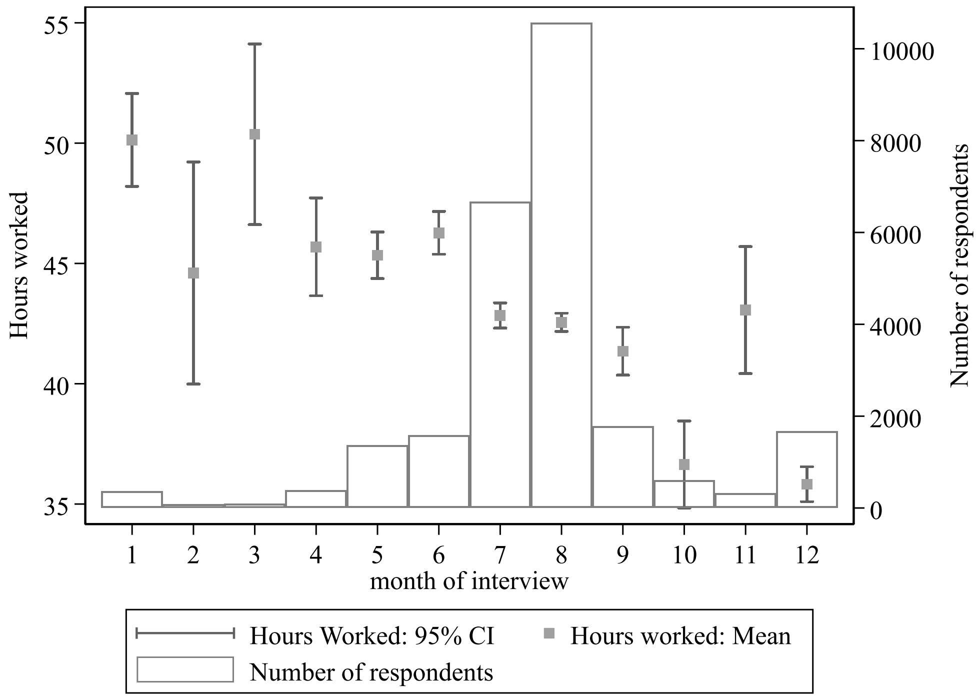
One common concern regarding self-reported working hours is the potential recall bias. Although the concern is very relevant, it is less likely to cause biased estimation, as along as the measurement error is not correlated with other explanatory variables, given that hours worked is the dependent variable of this study. However, recall bias or measurement error in hours worked do reduce the precision of our estimation, causing large standard errors and less power in identifying heterogeneous effect of pollution.

In our study, one potential cause of recall bias is the timing of interview. Although all the respondents are asked to recall the hours worked during the year prior to the interview, whether the interview is conducted during the busy- or off-season could significantly affect the hours reported. Figure C.1 shows the average hours reported by interview month, and we do observe some month-to-month variation. We note that the majority of the interviews were conducted in July and August, and the standard deviations for other months are large. We do not have perfect information on the busy/off season for each individual, but we take into account the seasonal variability in reporting by including province by interview month fixed effects.

Poor memory or cognitive function might be another source of inaccurate reporting in hours worked. To address this concern, we obtain the memory test score from a word recall test in the second wave (2012/2013) of CFPS.[17] We take the total score from the immediate word recall and delayed word recall to generate a memory score ranging from 0 to 20. As shown in Figure C.2, we observe that as the scores increase, the number of hours worked increases and so are the changes in hours worked. Simply assuming that higher memory score is an indicator for better cognitive function and ability to recall, we limit the sample to those with good memory, a score above median (8 out of 20), and we find a increase in the effect of $PM_{2.5}$ on hours worked from 0.48 hours in the baseline model to 0.63 hours as shown in Table C.1 column (1). However, this increase could be driven by the nature of jobs rather than ability to recall and it is also worth noting that cognitive function itself could be affected by pollution exposure.

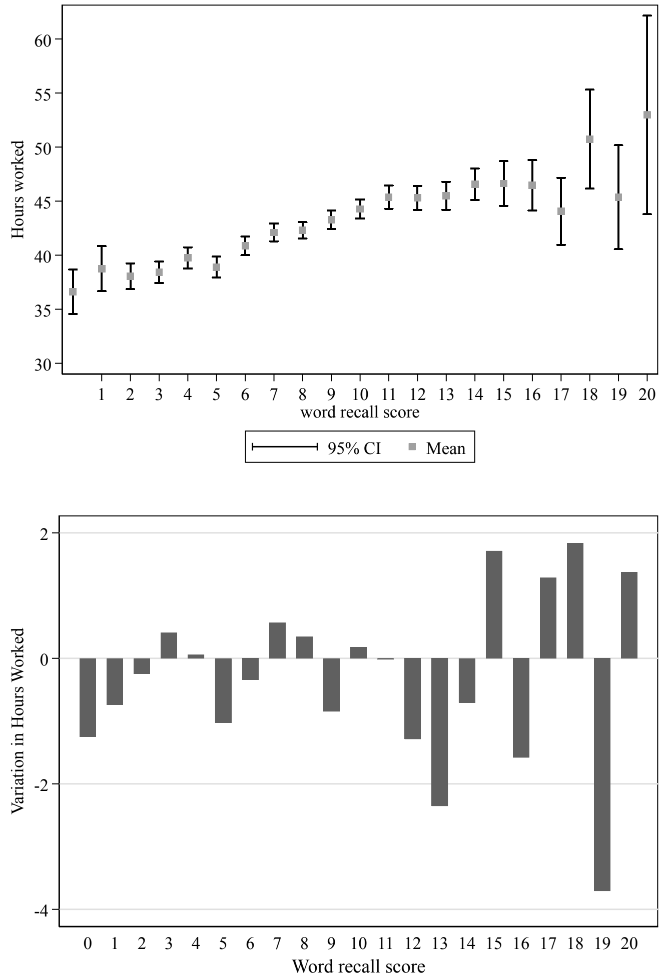
[17] No similar tests were conducted in the 2010 and 2014 surveys. By using the test score from the 2012 survey, we assume no major changes in cognitive function the two years before and after the test.

Figure C.1: Labor hours by month of interview



Note: The graph shows the average hours worked per week and the number of respondents by interview month.

Figure C.2: Hours worked and changes in hours worked by word recall scores



Note: The upper graph shows the average hours worked per week by word recall score and the lower graph shows the changes in hours reported by word recall score.

Table C.1: Recall Bias

	(1) Good Memory
$PM_{2.5}$	-0.630**
	(0.280)
Individual fixed effects	Yes
Province by interview month fixed effects	Yes
City by year fixed effects	Yes
N	14826

Note: The table presents the estimates for the sample with only above median word test scores. It includes individual fixed effects, county-year fixed effects, province-month fixed effects and time-varying individual controls such as age, age squared, education, marital status, whether the individual has dependents, whether the individual has more than one job and whether the individual works in agricultural or non-agricultural sector. The standard errors shown in parentheses are clustered at county level. Statistical significance is denoted by * for $p < 0.1$, ** for $p < 0.05$, *** for $p < 0.01$.