Particulate matter and labor supply: evidence from Peru*

Fernando M. Aragón[†] Juan Jose Miranda[‡] Paulina Oliva[§]

February 2016

Abstract

This paper examines the effect of air pollution on labor supply using the case of Lima, Peru. We focus on fine particulate matter ($PM_{2.5}$), an important air pollutant, and show that moderate levels of pollution reduce hours worked for working adults. The effect is concentrated among households with susceptible dependents, i.e., small children and elderly adults. This indicates that caregiving is likely a mechanism linking air pollution to labor supply. We find no evidence of intra-household attenuation behavior. For instance, there is no re-allocation of labor across household members, and earnings decrease. Finally, we show evidence of non-linearities in the dose response function: at higher concentrations, households without susceptible dependents also start experiencing negative effects.

*We thank the Comité de Gestión de la Iniciativa de Aire Limpio para Lima y Callao for sharing their pollution data. We are grateful to Thiemo Fetzer and seminar participants at UBC for useful comments and suggestions. The views expressed here do not necessarily reflect those of the World Bank or their member countries. All errors and opinions are our own.

†Department of Economics, Simon Fraser University; Email: faragons@sfu.ca

‡Environment and Natural Resources Global Practice, World Bank; Email: jjmiranda@worldbank.org

§Department of Economics, University of California, Santa Barbara and NBER; Email: paulina.oliva@ucsb.edu

1 Introduction

Existing evidence suggests that air pollution has negative effects on human health, especially for children and elderly adults.[1] A recent literature has also started to document negative effects among healthy adults in the form of reduction of labor productivity (Graff Zivin and Neidell, 2012; Adhvaryu et al., 2014; Chang et al., 2014; Li et al., 2015) and hours worked (Hanna and Oliva, 2015).[2] These findings, from the U.S., India, and Mexico, point to changes in labor outcomes as relevant pollution externalities.

In this paper we focus on the causal relationship between air pollution and hours worked. The empirical analysis of this relationship is complicated by two empirical challenges. First, there could be omitted variables that affect both air pollution exposure and the outcome of interest; which may bias the estimated response to air pollution. Second, households may move in response to air pollution according to their specific vulnerability introducing sorting bias.

These challenges have been addressed in a previous study with the help of an exogenous and sudden change in air pollution in Mexico City in the early nineties (Hanna and Oliva, 2015). This research design, however, limits the extent to which one can explore non-linearities in relationship between air pollution and hours worked as well as the mechanisms at play. This paper takes advantage of panel data on hours worked from Lima, Peru, to address the empirical challenges described above while preserving enough exogenous variation in pollution exposure to uncover the non-linear relationship between pollution and hours worked.

By comparing the shape of the dose-response function across different household compositions, we shed light on how age-specific vulnerabilities to air pollution can result in different labor supply responses to air pollution across households. We also explore whether intra-household substitution in labor supply can dampen the effects at the household level. Finally, the research design also allows us to focus on a somewhat newly monitored pollutant, fine particulate matter ($PM_{2.5}$), which has been shown to have some of the most adverse health effects in the medical literature (U.S. EPA, 2009), but for which there is relatively little economic research.[3]

[1] For a review of this literature see Currie et al. (2014) or Graff Zivin and Neidell (2013). There is also evidence that pollution can affect human capital. For instance, several studies link pollution to poorer school and cognitive outcomes (Almond et al., 2009; Lavy et al., forthcoming), and to increases in school absenteeism (Ransom and Pope, 1992; Gilliland et al., 2001; Park et al., 2002; Currie et al., 2009a).

[2] Previous work using data from U.S. cities also finds a positive and significant correlation between air particulates and work loss (Ostro, 1983; Hausman et al., 1984).

[3] Most of the economic literature focuses on total suspended particulates (Chay and Greenstone, 2003; Sanders, 2012), carbon monoxide (Currie and Neidell, 2005; Currie et al., 2009a; Currie et al., 2009b), and ozone (Lleras-

The panel structure of our data allows us to address the two empirical challenges described above by controlling for an array of time-varying omitted variables and relying on within household comparisons. First, we account for a wide range of city-wide and local time varying omitted variables through the inclusion of week and municipality-by-year fixed effects. Second, we include household fixed effects in our estimation which rules out bias through time-invariant omitted variables. Importantly, since our estimates are identified out of the within household time variation in air pollution, they are also free of sorting bias provided that changes in air pollution exposure over time are uncorrelated with household specific vulnerability (Wooldridge, 2005).

We find that, even at moderate concentrations, air pollution reduces labor supply. The effect is concentrated among households with dependents more susceptible to pollution, i.e., small children and elderly adults. The magnitude is economically significant. For instance, an increase in $PM_{2.5}$ of 10 $\mu g/m^3$ is associated to a reduction of almost 2 hours worked per week. The effect of air pollution on individuals with susceptible household members appears linear. In contrast, the effect of pollution on labor supply of workers in households without susceptible individuals is non-linear, and only appears to respond to high levels of pollution (above 75 $\mu g/m^3$). This observation points to the extensive margin as a potential source of non-linearities in the relationship between air pollution and labor supply: as pollution levels increase, the effects on labor supply expands beyond households with susceptible individuals to the rest of the population.

These findings are consistent with evidence suggesting that children and elderly adults' health is more susceptible to air pollution, and thus may be affected at lower concentrations than healthy adults (U.S. EPA, 2009, Ch. 8). Our results suggest that the mechanism linking low levels of air pollution to labor supply is the increase in demand for caregiving: healthy adults reduce hours of work to take care of sick dependents. However, at higher concentrations, the link is more direct: pollution directly harms the health of those who participate in the workforce. To corroborate these findings, we use auxiliary data from the Demographic and Health Survey (DHS) on health outcomes for the same city and period. We find that $PM_{2.5}$ is associated with an increase in respiratory diseases among small children.

Finally, we examine whether households respond to this shock by re-allocating caregiving

Muney, 2010; Graff Zivin and Neidell, 2012). Other studies focus on NO_x (Deschenes et al., 2012), SO_2 (Hanna and Oliva, 2015) and aerosols (Jayachandran, 2009). Among the few studies focusing on $PM_{2.5}$ are Zweig et al. (2014), Chang et al. (2014), Adhvaryu et al. (2014), Lavy et al. (forthcoming) and Li et al. (2015).

duties and labor supply among their members. For instance, a household may shift caregiving to workers with relatively worse earning opportunities to minimize the negative shock in earnings, and consumption. However, we find no evidence of intra-household substitution of hours worked in response to air pollution shocks. There are no significant differences in the effect of pollution associated with age, gender, education, or position within the household. Consistent with the net reduction in hours worked within households, we find a negative effect of air pollution on earnings.

The rest of the paper is organized as follows. Section 2 provides background information on particulate matter and pollution in Lima city. Section 3 describes the data and discusses the empirical strategy. Section 4 presents the main results, while Section 5 concludes.

2 Background

2.1 Fine particulate matter

In this paper, we focus on the effect of fine particulate matter ($PM_{2.5}$) on labor supply. This is motivated by the evidence linking it to respiratory and cardiovascular diseases.[4]

$PM_{2.5}$ is an air pollutant that consists of tiny particles less than 2.5 micrometers in diameter.[5] It can be produced by natural sources, like wildfires, but it largely comes from the combustion of fossil fuels and chemical reactions of air emissions. The concentration of $PM_{2.5}$ in a given location is affected by proximity to its main sources but also by other local environmental factors, such as wind speed and direction, air temperature, humidity, precipitation and vegetation (Beckett et al., 2000; Hien et al., 2002; Janhäll, 2015). These factors create potential for seasonal and intra-urban variations in $PM_{2.5}$ levels (Vecchi et al., 2004; Wilson et al., 2005).

Given their small size, $PM_{2.5}$ can penetrate deep into the lungs and into the bloodstream (Bell et al., 2004). Moreover, it is harder to avoid than other pollutants since it can easily penetrate indoors (Thatcher and Layton, 1995; Vette et al., 2001). These features make it a particularly harmful pollutant (Bell et al., 2004; Pope III and Dockery, 2006).[6]

A large medical literature finds evidence of a causal effect of short term exposure to $PM_{2.5}$

[4]However, we also explore other air pollutants such as PM_{10}, nitrogen dioxide (NO_2) and sulfur dioxide (SO_2), see Section C.

[5]Other types of particulate matter include PM_{10} and coarse particulate matter ($PM_{2.5-10}$).

[6]See U.S. EPA (2009) for a comprehensive review on health effects of particulate matter.

on cardiovascular and respiratory diseases, as well as an increase in mortality (U.S. EPA, 2009, Ch. 2).[7] These negative health effects are particularly important among susceptible populations, such as children, elderly adults, and people with pre-existing conditions like asthma and cardiovascular or lung disease. These populations are at increased risk for the detrimental effects of ambient exposure to particulate matter (U.S. EPA, 2009, Ch. 8). The effects are not necessarily immediate; several studies find a lag between exposure to particulate matter and hospital admissions. There is, however, no consensus on a priori lag times to use when examining morbidity. Some studies find short lags, 0 to 1 days, for cardiovascular diseases and for elderly patients with other diseases, and larger lags, from 3 to 5 days, for asthma hospital admissions.

2.2 Air pollution in Lima

Lima is Peru's capital and, with a population of more than 9 million, its largest city. It is also heavily polluted. For instance, during the period of this study (2007-2011), the average daily level of $PM_{2.5}$ was around 45.6 μg/m^3. This level is above the U.S. 24-hour standard of 35 μg/m^3 and is considered unhealthy for susceptible groups (U.S. EPA, 2012). In fact, in around 70% of weeks $PM_{2.5}$ levels in Lima exceeded this threshold (see Figure 1).[8] The main source of air pollutants is exhaust from motor vehicles. According to some official estimates, this source accounts for more than 80% of total emissions in the city (CONAM, 2001). The rest is produced by point sources such as power plants and industrial sites.[9]

There are several features relevant for empirical analysis. First, the distribution of $PM_{2.5}$ has a wide support with common episodes of moderate to high concentrations (see Figure 2). This feature allows us to study the relationship between pollution and labor supply at different levels of $PM_{2.5}$ and explore non-linearities in the dose-response function.

Second, there is intra-urban variation in $PM_{2.5}$ levels. Areas in the north, center, and east side of the city have higher exposures to $PM_{2.5}$ than areas in the south and closer to the sea shore (like Callao). This is likely driven by the presence of industrial sites in the east side and

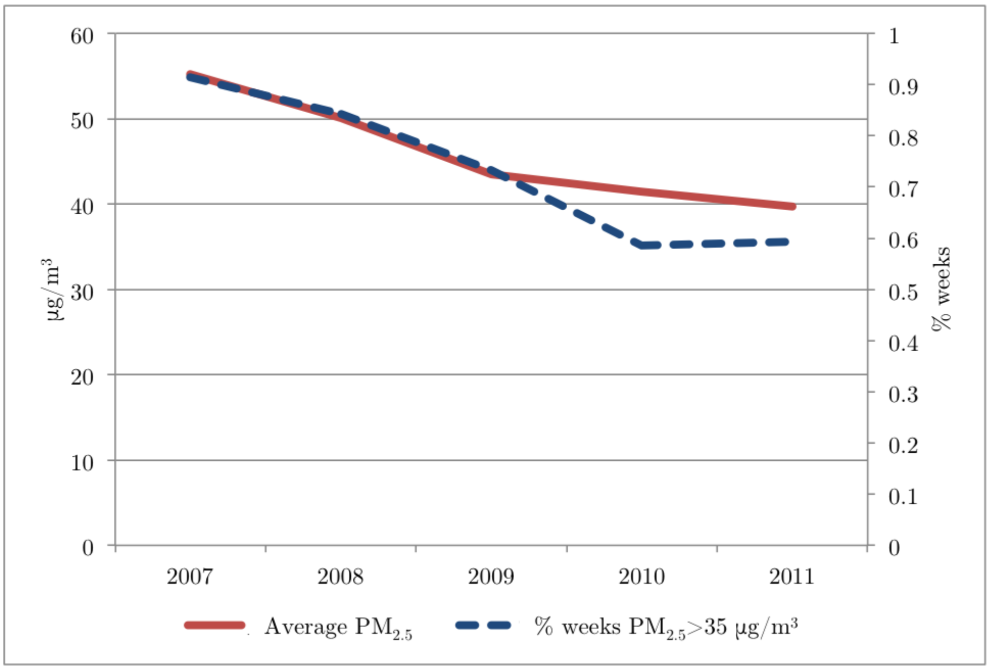
[7] In contrast, the evidence linking other sizes of particulate matter to health problems is considered only suggestive or inadequate.

[8] Similarly, levels of other air pollutants such as $PM_{2.5}$ and NO_2 are above international standards. However, levels of SO_2 are very low (DIGESA, 2012). See Figures A.1, A.2 and A.3 in the Appendix for distribution of other air pollutants.

[9] These estimates refer to total air emissions not only to $PM_{2.5}$.

.

Figure 1: Evolution of $PM_{2.5}$, years 2007-2011



prevailing winds from the sea that disperse air pollutants inland (Sánchez-Ccoyllo et al., 2013).[10] Third, there is also significant temporal variation most of which comes from seasonal changes in meteorological conditions and a downward trend in air pollution over the last years (see Figure 1).[11] However, week and municipality-specific year fixed effects will absorb a large amount of this variation; leaving behind just the short-run deviations with respect to city-wide patterns for identification.

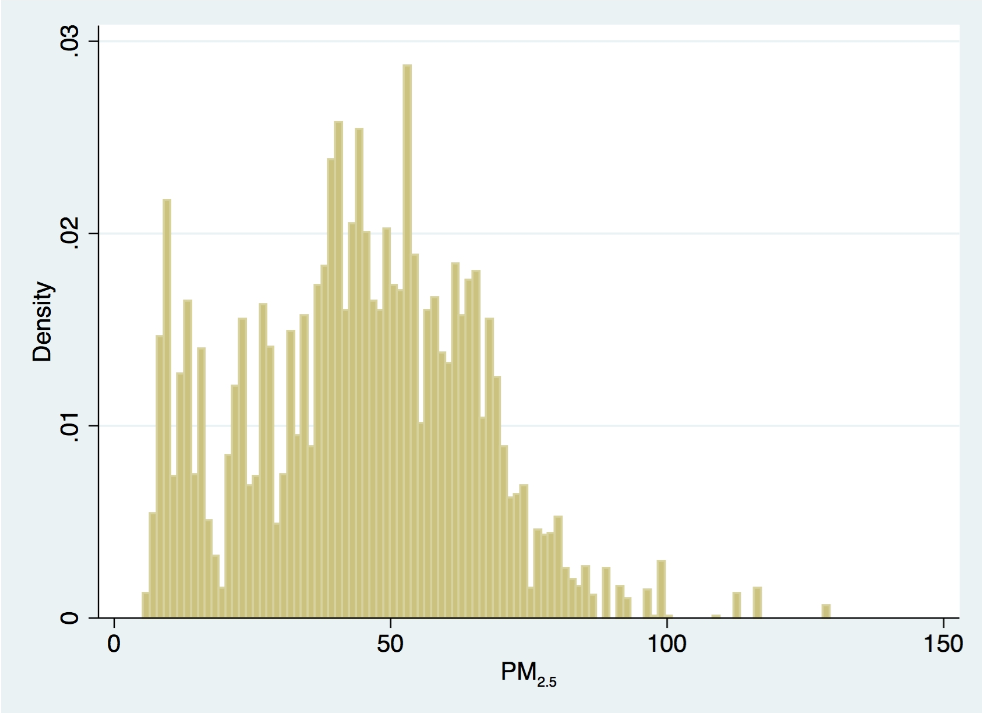
Finally, during the period of analysis, there was no system of public information on air pollution. The Meteorological Agency (SENAMHI) did not begin broadcasting daily reports on air quality until November 2011 (Aranda, 2011).[12] This reduces the likelihood that labor supply responded in anticipation to air pollution levels.

[10]See Figure A.4 in Appendix for average $PM_{2.5}$ levels reported by monitoring stations in different locations. Results from a recent atmospheric dispersion model also suggest similar spatial distribution (DIGESA, 2012).

[11]In the period of analysis, levels of $PM_{2.5}$ peaked in Fall months. The reduction in air pollution might be due to replacement of old vehicles by newer ones, and increasing use of natural gas as fuel for transportation, electricity generation, and industrial operations.

[12]The monitoring stations used in this study were installed and operated by an agency of the Ministry of Health (Dirección General de Salud - DIGESA), as part of a pilot project. SENAMHI's monitoring stations were installed between 2010 and 2011.

Figure 2: Distribution of weekly average $PM_{2.5}$ (in $\mu g/m^3$), years 2007-2011



3 Methods

3.1 Data

Labor and health data We use micro-data from the Peruvian National Household survey (ENAHO). This survey covers years 2007 to 2011 and includes geographical coordinates of households' residences at the level of a census block. The survey is collected on a continuous basis, thus the sample includes households interviewed in different months of the year. We focus on the panel sample collected in Metropolitan Lima. This is a random sample of almost 900 households (or around 14% of the total household sample) tracked for two or more years.[13]

Our measure of labor supply is number of hours worked in the last seven days. We construct this measure for all individuals in the labor force.[14] In the case where individuals are unemployed, number of hours worked is equal to zero. The ENAHO survey also includes other socio-demographic characteristics such as employment status, type of occupation, monthly earnings, schooling, age, gender, etc. We use some these variables as controls or ancillary outcomes

[13]The panel sample is unbalanced. The majority of households are observed only two years (n=586) or three years (n=180).

[14]This includes individuals age 14 to 65 who are either working or looking for a job.

in our baseline regression.

To obtain measures of health, we use the Demographic and Health Survey (DHS) for 2007-2009.[15] This survey also includes geographical coordinates of each household's residence. However, the location is randomly displaced by up to 3 kilometers. This introduces an additional measurement error. The DHS contains self-reported information on children's health conditions in the last 2 weeks. Based on these data, we construct indicators of having an acute respiratory disease (i.e., cough accompanied by short breath), fever, diarrhea, or anemia.[16]

Pollution data We obtain daily measures of key pollutants such as $PM_{2.5}$, PM_{10}, nitrogen dioxide (NO_2) and sulfur dioxide (SO_2) for years 2007-2011. These measures provide average levels of pollutants for a 24 hour-period and were collected every 2-3 days each week.[17]

The air pollution data come from five monitoring stations installed and operated by an office of the Ministry of Health (Dirección General de Salud - DIGESA). The monitoring stations were located in the four cardinal points of the city plus one in the city center (see Figure 3).

Note that these monitoring stations were installed as part of the first project to systematically measure air quality in Peru.[18] We complement this dataset with data on monthly average temperature and humidity collected by SENAMHI.

Matching labor, health and pollution data To construct the measure of pollution for a given household, we first define the reference period for labor outcomes. This corresponds to the seven days prior to the interview date. We call this reference period week t. Then we obtain the average level of a pollutant from monitoring stations in week $t-1$.[19] Thus, we use exposure to pollutants in the week before labor outcomes are realized. This responds to previous evidence

[15]We cannot use other years due to lack of geographical information.

[16]The ENAHO survey also contains self-reported information on health conditions, such as illnesses or accidents in the last 4 weeks. However, we do not use this information due to its longer time horizon, which difficult to match with environmental conditions, and because it does not distinguish between respiratory and non-respiratory diseases.

[17]The collection dates in a given week were randomly chosen. The collection process was done by trained personnel of the Ministry of Health using active air sampling procedures. The detailed data collection protocol is available at `http://www.digesa.sld.pe/norma_consulta/protocolo_calidad_de_aire.pdf`.

[18]As mentioned in Section 2.2, the meteorological agency (SENAMHI) started regular, hourly, collection of air quality indicators only since late 2011. We cannot use these new air quality data due to lack of georeferenced labor data for this period.

[19]We also examine the results using other lags and leads. We find that the only significant effect is obtained when using one-week lag. These results are available upon request.

suggesting a lag of a few days between exposure to pollution and health problems.[20] Finally, we take a weighted average of pollution levels of stations in the vicinity of the households. We use only data from stations within 8 kilometers of a household. Similar to previous work, we use an inverse distance interpolation method.[21]

We trim some extreme and abnormal observations.[22] In particular, we drop observations with top 1% values of pollution and hours worked. We also drop observations from one station (located in the city center) for years 2007-2009 due to data collection problems and unusually volatile observations.[23] We use observations for this station for years 2010 and 2011 only.

Figure 3 displays the map of Lima city with the location of monitoring stations and census blocks both in the whole sample (yellow dots) and in the final sample used for this study (blue dots). Note that the final sample does not include observations located far from monitoring stations, especially in the north and east, but it is, otherwise, dispersed across the city.[24]

3.2 Empirical strategy

The objective of the empirical analysis is to identify the causal effect of exposure to air pollution on labor supply. The first challenge that we face in achieving this is the likely presence of unobservable factors that may affect both pollution and number of hours worked. For instance, wealthier, better educated households may locate in less polluted areas. There could also be time-varying characteristics, such as seasonal variations in weather and health or local trends in labor markets and pollution levels that may create a spurious correlation between air pollution and labor supply.

Our empirical strategy addresses this potential source of endogeneity in two ways. First, we include a rich set of time-varying controls, such as temperature, humidity, week fixed effects and municipality-by-year fixed effects. Thus, our estimates are not subject to bias from any unobservable determinant of labor supply that is time varying but common across all households in Lima. As we control for municipality-by-year fixed effects, our estimates are also robust to the

[20] In the case of health outcomes, the reference period is two weeks before the interview date (i.e. weeks t and $t-1$). In that case, we use measures of pollution in weeks $t-1$ and $t-2$.

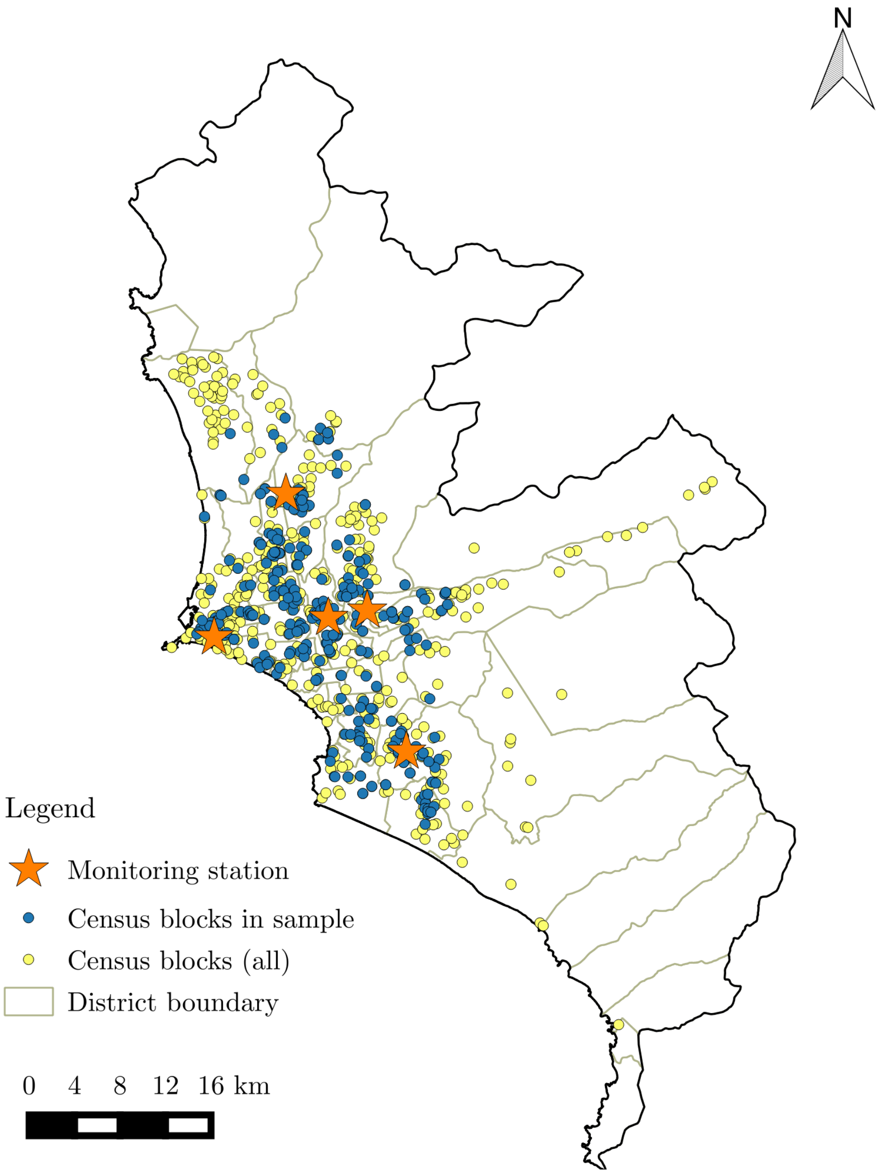
[21] We use the inverse of the Euclidean distance between the household and a monitoring station as weights.

[22] Using all available data produces similar, but less precise, results.

[23] According to communications with DIGESA's personnel, from 2007 to 2009 this monitoring station was located in a place that did not fulfill the conditions stipulated in the data collection protocol. For this reason, the station was re-located in 2010.

[24] The final sample is not necessarily representative of Lima city given the changes made to the original sample, i.e., exclusion of areas further away from monitoring stations and non-panel observations.

Figure 3: Map of Lima city with monitoring stations and Census blocks



presence of local labor supply determinants that evolve slowly over time, such as gradual changes in labor markets or differential growth across municipalities. Second, we include household fixed effects in our baseline regression. This effectively controls for all time-invariant omitted factors that could bias our results such as demographics, preferences for air pollution, etc.

In addition to the classic omitted variables problem, which stems from the potential correlation between unobservable determinants of labor supply and air pollution, there could be bias in the OLS estimates stemming from heterogeneous responses to air pollution: correlated random coefficients. However, since our identification rests on within-household differences in air pollution exposure, the identification assumption we require is no correlation between household specific vulnerability and the changes in air pollution exposure experienced over time. As households in our sample do not move, it is likely that any changes in air pollution experienced will be orthogonal to household-specific vulnerability.[25]

We estimate the following baseline regression:

$$hours_{ij,t} = \alpha_j + \beta PM2.5_{j,t-1} + \gamma \mathbf{X}_{ij,t} + \epsilon_{ij,t}, \tag{1}$$

where the unit of observation is individual i, in household j, and t is the reference week for labor outcomes, i.e., 7 days before the interview date. The main outcome is the number of hours worked, $hours_{ij,t}$ although in some specifications we also use other outcomes, such as labor force participation or employment status. $PM2.5_{j,t-1}$ refers to the measure of fine particulate matter ($PM_{2.5}$) to which the household was exposed in the week before labor outcomes were realized. Our main specification uses the average level of $PM_{2.5}$, but we also use discrete measures, such as an indicator of whether the levels exceeded the U.S. standard (i.e. 35 μg/m^3) or a step function of the average $PM_{2.5}$. Equation (1) includes household fixed effects, α_j, and a set of time-varying fixed effects, weather and individual controls, $\mathbf{X}_{ij,t}$.[26] We cluster the errors at the municipality level to account for spatial and serial correlation and use sampling weights in all estimations.[27]

At the core of our analysis is the recognition that the effect of particulate matter on labor

[25]There might be, however, a problem of selection bias due to attrition from the panel sample. This could happen, for example, if households exposed to higher levels of pollution are more likely to re-locate and thus to drop from the panel sample. In Section 4.2 we test, and rule out, this form of selection bias.

[26]For a detailed list of control variables see notes of Table 2.

[27]We also check the robustness of our results to using Conley standard errors (see Table 4).

supply may be heterogeneous and uncovering systematic patterns for this heterogeneity can shed light on the mechanisms behind this relationship. As discussed in Section 2, some populations, such as small children and elderly adults, are more susceptible to health problems when exposed to particulate matter. These population groups are usually not part of the labor force thus pollution cannot affect their labor supply. However, it can *indirectly* affect labor supply of other household members by increasing demand for caregiving: parents or older siblings may miss work to take care of a sick child or elderly relative. In that case, we would observe a negative effect of pollution on labor supply even for levels at which adult workers' health is not affected. We examine this heterogeneity by splitting the sample between households with and without susceptible individuals. We classify a household as having a susceptible individual if at least one household member is a small child (5 years or younger) or an older person (75 years or older).

Table 1 displays the mean of key environmental and socio-economic variables for the whole sample and for the sample of households with and without susceptible individuals.[28] Note that there are not significant differences between both groups on exposure to pollutants or labor outcomes, such as participation rates, employment rates, or number of hours worked. There are, however, statistically significant differences in some observable characteristics such as poverty headcount, workers' age, and household size.[29]

[28]See Table B.1 in Appendix for the mean of children's health indicators.
[29]In Section 4.2 we examine the importance of these differences on explaining the results.

Table 1: Mean of environmental and socio-economic variables

Variable	All	Household has susceptible individual		p-value mean comparison
		Yes	No	(2)=(3)
	(1)	(2)	(3)	(4)
Pollution and weather				
$PM_{2.5}$	45.5	46.0	45.2	0.446
$PM_{2.5}$ above 35 $\mu g/m^3$ (%)	71.1	71.5	70.8	0.750
PM_{10}	80.3	79.5	80.8	0.666
SO_2	20.0	20.8	19.5	0.247
NO_2	24.0	24.1	24.0	0.849
Temperature (Celsius)	19.1	19.2	19.0	0.180
Humidity (%)	81.4	81.5	81.4	0.257
Individuals in working age				
Labor force (%)	74.2	74.5	73.9	0.503
Individuals in labor force				
Employed (%)	99.8	99.7	99.8	0.857
Hours worked	43.6	44.0	43.3	0.443
Has secondary job (%)	11.2	11.7	10.8	0.375
Is independent worker (%)	33.6	34.7	32.8	0.202
Earnings in last month	1067.2	1002.8	1111.2	0.008
Age	38.0	36.5	39.0	0.000
Schooling (years)	11.4	11.4	11.3	0.891
Is female (%)	45.4	45.8	45.0	0.312
Is household head (%)	35.7	32.4	37.9	0.000
Households				
Poverty headcount (%)	15.5	24.5	10.2	0.000
Number of income earners	243.4	255.9	236.0	0.000
Household size	4.3	5.2	3.7	0.000
Nr. observations	5,218	2,167	3,051	

Notes: $PM_{2.5}$, PM_{10}, SO_2 and NO_2 are measured in $\mu g/m^3$. These measures of pollution are 7-day averages for week $t-1$, where t is the reference week for labor outcomes. Temperature and humidity are monthly averages. Earnings are measured in Nuevos Soles (PEN). Susceptible individuals include children 5 years and younger, and seniors 75 years and older. Number of observations refer to individuals in the labor force. Column 4 displays p-values of mean comparison tests. Means are obtained using sampling weights.

4 Results

4.1 Main results

Table 2 presents the main results. We split the sample between individuals in households with and without susceptible individuals and use two alternative measures of exposure to pollution: average weekly $PM_{2.5}$ and an indicator of $PM_{2.5}$ exceeding the U.S standard (35 $\mu g/m^3$). In both cases, there is a negative and significant relationship between exposure to $PM_{2.5}$ and hours worked but only for individuals in households with susceptible individuals. For individuals in households without susceptible individuals, there is no significant linear relationship. To the extent that the set of covariates and fixed effects control for relevant omitted variables, we can interpret these results as the causal effect of $PM_{2.5}$ on labor supply.

The magnitude of the effect is economically relevant. A reduction of $PM_{2.5}$ of 10 $\mu g/m^3$ is associated with an increase of 1.9 hours of work per week for workers in households with susceptible individuals.[30] This group represents a sizable proportion of the population: around 40 percent. Given the observed levels of pollution in Lima, our results imply that, for individuals with susceptible dependents, a reduction of average $PM_{2.5}$ to levels compliant with U.S. standards would increase hours worked by almost 7 hours a week.[31]

Our results suggest heterogeneous effects by presence of susceptible individuals. To formally test for the statistical difference in coefficients across demographic groups, we estimate a model using the whole sample and include a full set of interactions with an indicator for households with susceptible individuals. The results, shown in third row in Table 2, suggest that the magnitude of the effect of $PM_{2.5}$ on hours worked is indeed significantly larger for individuals in households with susceptible individuals.

We interpret this result as evidence that a mechanism linking pollution to labor supply is caregiving: workers may reduce hours of work to take care of sick dependents, whose health is more susceptible to air pollution. This is a plausible explanation given previous findings of the negative effect of air pollution on health, specially of children and elderly adults.

[30] At average values, this result implies a pollution elasticity of labor supply of -0.167. As a comparison, Hanna and Oliva (2015) find SO_2 pollution elasticities of labor supply ranging from -0.138 to -0.172 for Mexico city. In contrast, Chang et al. (2014) find no effect of $PM_{2.5}$ on labor supply among pear packers in California. This insignificant result may be due to relatively lower concentrations of pollutants and a non-linear relationship between pollution and labor supply. The average $PM_{2.5}$ in their context is 10.06 $\mu g/m^3$ while in the Peruvian case the average is 45.6 $\mu g/m^3$.

[31] This figure is obtained from Column 3 in Table 2.

Table 2: Main results: effect of $PM_{2.5}$ on hours worked

	Hours worked			
	(1)	(2)	(3)	(4)
PM 2.5	-0.192***	-0.039		
	(0.046)	(0.050)		
PM 2.5 above 35 μg/m^3			-6.817***	-0.107
			(2.279)	(1.635)
Difference (1)-(2) or (3)-(4)	-0.144**		-6.388**	
	(0.071)		(2.924)	
Household has susceptible individuals	Yes	No	Yes	No
Observations	2,167	3,051	2,167	3,051
R-squared	0.429	0.447	0.429	0.447

Notes: Robust standard errors in parentheses. Standard errors are clustered at the municipality level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. Baseline specification includes household, week and municipality-by-year fixed effects, characteristics of individual (gender, age, age^2, schooling, schooling^2, type of household member, indicator for having a second job, indicator of being independent worker), and monthly temperature and humidity. Third row displays difference of estimates for both samples obtained from a model with full interaction terms. PM 2.5 is average $PM_{2.5}$ in week $t-1$, where t is the week of reference of labor outcomes. PM 2.5 above 35 μg/m^3 is an indicator equal to 1 if average $PM_{2.5}$ in week $t-1$ exceeded the U.S. standard.

We further examine the validity of this interpretation by exploring the effect of $PM_{2.5}$ on children's health.[32] To do so, we use data on self-reported children morbidity from the DHS. Our main outcome is the presence of cough accompanied with short breath. This is a common indicator of acute respiratory disease. As a falsification test, we also estimate the effect of $PM_{2.5}$ on other diseases, not linked to short term exposure to air pollution, such as fever, diarrhea, and anemia. Our empirical specification is similar to (1) but there are some changes due to the limitations of the DHS dataset.[33] In particular, we include as covariates month and year fixed effects, weather controls, and children and mother's characteristics, but do not include household, week, or municipality-by-year fixed effects.[34] As measures of exposure to pollution we use an indicator of average $PM_{2.5}$ exceeding the U.S. standard and the log of average $PM_{2.5}$.[35]

Table 3 displays the results. Consistent with the existing literature, we find a positive and significant relationship between exposure to $PM_{2.5}$ and our indicator of acute respiratory disease, but there is no significant relationship with other non-respiratory diseases. The magnitude of this relationship is sizable. According to our results, reducing $PM_{2.5}$ to the compliance level with the U.S. standards would lead to a 9 percent reduction in the incidence of acute respiratory diseases. This represents almost half the average incidence.

4.2 Additional checks

Our identification assumption would be violated in the presence of confounding, unobserved, omitted determinants of labor supply that vary over time within census blocks. In other words, if there were omitted variables that have not been fully accounted for by the rich set of fixed effects (week and municipality-by-year). We address this concern in two ways. First, we add a richer set of time-varying controls, namely, quarter-by-year fixed effects and non-parametric trends interacted with observable characteristics, such as poverty status, number of income earners, and worker's age. The results, however, are similar (see column 1 in Table 4). Second,

[32] We are, however, unable to examine the effect on adults and the elderly due to data limitations. The DHS only covers morbidity of children 5 years and younger, while the ENAHO's health data covers a long reference period and does not distinguish respiratory diseases.

[33] The main limitations are that (1) the DHS does not have a panel sample, (2) covers fewer years (2007 to 2009), (3) the sample is not distributed over the whole year, and (4) household's locations are randomly displaced. These features prevent the use of household or week fixed effects, and difficult matching the household to a given municipality.

[34] See notes of Table 3 for additional estimation details.

[35] Results are similar using a more flexible specification with a step function of $PM_{2.5}$ similar to the one used in Section 4.3, see Table B.2 in the Appendix.

Table 3: $PM_{2.5}$ and children's health

	Cough and short breath (1)	Fever (2)	Diarrhea (3)	Anemia (4)
Panel A				
PM 2.5 above 35 mg/m3	0.093**	0.039	0.025	-0.001
	(0.047)	(0.054)	(0.034)	(0.074)
Observations	712	712	712	492
R-squared	0.053	0.060	0.067	0.238
Panel B				
ln(PM 2.5)	0.073*	0.008	0.007	-0.054
	(0.042)	(0.043)	(0.035)	(0.056)
Observations	712	712	712	492
R-squared	0.053	0.060	0.067	0.240

Notes: Robust standard errors in parentheses. Standard errors are clustered at the survey block level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions are estimated using OLS and include month and year fixed effects, individual controls (age and gender of child, mother's age, indicators of household wealth, indicator for a smoking mother), and logs of monthly temperature and humidity. PM 2.5 refers to average $PM_{2.5}$ in weeks $t-1$ and $t-2$, where t is the period of 7 days prior to interview. Note that reference period for morbidity questions is weeks t and $t-1$. Panel A uses an indicator of PM 2.5 being above the U.S. standard, while Panel uses log of PM 2.5.

we examine the relationship between *contemporaneous* exposure to pollution and hour worked. Note that an important omitted variable is local level of traffic. High traffic could raise air pollution and, by increasing transportation costs, also reduce labor supply. This alternative explanation would imply a contemporaneous relation between these two variables. However, the relationship is small and statistically insignificant (see column 2 Table 4).[36]

Columns 3 through 5 in Table 4 check the robustness of our results to alternative specifications. Results are robust to using non-linear functions of weather, a narrower definition of susceptible population, and using a log-linear specification. In column 6, we also test alternative variance structures, and estimate standard errors using the procedure suggested by Conley (1999).[37]

A key finding is that $PM_{2.5}$ has different effects on hours worked in households with and without susceptible dependents. As discussed in Section 3.2, there are some observable differences between these two types of households. Households with susceptible dependents tend to have more income earners, relatively younger workers, and be slightly poorer. A relevant concern is that these differences, not the presence of susceptible individuals, are driving the heterogeneous results. This could happen, for instance, if poverty, worker's age or household size influence how pollution affects labor supply.

We examine this alternative explanation by estimating a model using individuals in both types of households and adding interactions of $PM_{2.5}$ with an indicator of having a susceptible individual and other observable characteristics (see Table B.3 in the Appendix). This specification allows us to examine other sources of heterogeneous effects of air pollution. Results, however, confirm the original findings: $PM_{2.5}$ only seems to reduce hours worked among individuals in households with susceptible individuals.

Finally, we examine sample attrition as a source of selection bias. Note that, by using a panel sample and household fixed effects, we reduce concerns of residential sorting bias, i.e, bias due to systematic household differences that are correlated with exposure to pollution. However, households may drop from the panel sample in a systematic way. For example, wealthier, better educated, households may be more able to re-locate in response to changes in air pollution, and thus be more likely to drop from the panel sample. To the extent that

[36]Results are also insignificant when using average $PM_{2.5}$ in weeks $t+1$ or $t+2$.

[37]We use the STATA ado file *reg2hdfespatial* developed by Fetzer (2014) and based on Hsiang (2010). We use a 1 year time lag and a distance cutoff of 8 kilometers.

Table 4: Additional checks

	Hours worked					
	(1)	(2)	(3)	(4)	(5)	(6)
A. Households with susceptible individuals						
PM 2.5	-0.152***		-0.188***	-0.161**		-0.167***
	(0.053)		(0.052)	(0.062)		(0.049)
Contemp. PM 2.5		-0.042				
		(0.046)				
Log(PM 2.5)					-7.478***	
					(1.746)	
Observations	2,167	2,245	2,167	1,817	2,167	2,167
R-squared	0.436	0.422	0.430	0.425	0.429	0.202
B. Households without susceptible individuals						
PM 2.5	-0.019		-0.038	-0.053		-0.027
	(0.063)		(0.053)	(0.044)		(0.035)
Contemp. PM 2.5		0.004				
		(0.045)				
Log(PM 2.5)					-0.501	
					(1.614)	
Observations	3,051	3,078	3,051	3,401	3,051	3,051
R-squared	0.451	0.432	0.447	0.447	0.447	0.178
Model	Additional time-varying controls	Contemp. PM 2.5	Quadratic polynom. weather	Suscept.= children under 5	Semi-log specif.	Conley S.E.

Notes: Robust standard errors in parentheses. Standard errors are clustered at the municipality level, except in Column 6 in which they are estaimted using the procedure proposed by Conley (1999). * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions include the same controls as the baseline specification (see notes of Table 2. Panel A and B use two different samples. Unless specified, PM 2.5 refers to average $PM_{2.5}$ in week $t-1$, where t is the week of reference of labor outcomes. Column 1 adds quarter-by-year fixed effects and year fixed effects interacted with indicators for being poor, having a number of income earners above the median, and above-median age. Column 2 uses the contemporaneous value of $PM_{2.5}$, i.e., the average value during the reference week for labor outcomes. Column 3 adds temperature and humidity squared to the baseline regression. Column 4 defines as susceptible individuals only children 5 years and younger. Column 6 estimates model without sample weights.

attrition is correlated with hours worked, this behavior would bias our results. We test for attrition bias following the procedure suggested by Verbeek and Nijman (1992), and described in Wooldridge (2002, Ch.17.7.2). This requires adding to the baseline regression an indicator equal to 1 if the household drops from the panel sample in the next period. Under the null hypothesis that attrition is not systematic, this additional explanatory variable should not be significant. We find that indeed this variable is insignificant and thus we fail to reject the null hypothesis. This result weakens concerns of attrition bias being a relevant issue (see Table B.4 in the Appendix).

4.3 Non-linearities

The previous results provide evidence of the *average* effect of $PM_{2.5}$ on labor supply. However, these effects could be different at higher levels of pollution. This could happen, for instance, if health problems only become severe enough to require hospitalization or preclude work when pollution is sufficiently high. It could also be that different demographic groups react to different "critical" levels of air pollution.

To examine non linearities, we estimate the baseline model (1) replacing the main explanatory variable with a step function of $PM_{2.5}$. In particular, we estimate the following model:

$$hours_{ij,t} = \alpha_j + \sum_k \beta_k PM2.5^k_{j,t-1} + \gamma \mathbf{X}_{ij,t} + \epsilon_{ij,t}, \tag{2}$$

where $PM2.5^k_{j,t-1}$ is an indicator equal to 1 if average $PM_{2.5}$ in week $t-1$ is in bracket k.[38] Similarly to the baseline results, we split the sample between individuals in households with and without susceptible dependents.

Figures 4a and 4b display the estimates of β_k for both samples.[39] There are two important observations. First, for individuals with susceptible dependents (i.e., small children and elderly adults) the relationship between pollution and labor supply seems to be linear. The effect is negative and statistically significant even at moderate levels (i.e., around average). However, for individuals without susceptible dependents, the relationship is non-linear. At moderate levels

[38]We define the following brackets $k = \{0-35, 35-45, 45-55, 55-75, 75+\}$. We define these brackets based on the breakpoints used in the U.S. Air Quality Index (U.S. EPA, 2012) and the constraint of having enough observations in each bracket.

[39]See Table B.5 in Appendix for the regression estimates.

(i.e., below 75 μg/m^3), there is no effect of PM 2.5 on hours worked. But, at higher levels (above 75 μg/m^3) the effect becomes negative and significant.

We interpret these results as evidence that, at moderate levels, the mechanism linking pollution to labor supply is caregiving. But, at higher levels the link is more direct: pollution may reduce labor supply by harming workers' health. This interpretation is consistent with existing epidemiological evidence suggesting that higher levels of pollution are required to affect the health of non-susceptible populations.[40] Moreover, this finding points to the extensive margin as a potential source of non-linearity in the relationship between air pollution and labor supply: as pollution levels increase, the effects on labor supply expands beyond households with susceptible individuals to encompass the rest of the population.

4.4 Attenuation behavior

An important question is whether households attenuate the negative, short-term, impact of pollution on labor supply through intra-household substitution of labor. This would occur, for instance, if households reallocate caregiving duties to household members with relatively worse labor opportunities. This would reduce the negative shock on labor supply of main providers, and the associated reduction on earnings and consumption.

To illustrate this argument consider this simple model. There is a unitary household with two individuals $i = 1, 2$. Each individual has 1 unit of time that can be sold to labor markets, L_i, at wage w_i or used as domestic work, h_i, to provide a household service, namely, care for dependents.[41] The minimum amount of care that the household must provide is s. For simplicity, we assume that the technology that transforms domestic work into caregiving is defined by $f(h_1, h_2) = h_1^{\rho} h_2^{1-\rho}$, with $\rho \in (0, 1)$.[42] Household utility, $U(c)$, depends of total consumption, c.

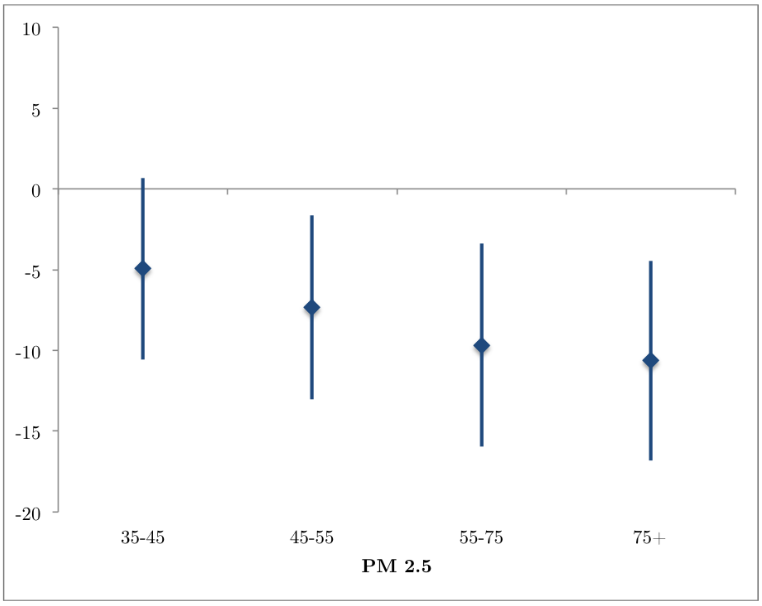
The household's allocation of domestic work, and thus choice of each individuals' labor

[40]For example, the U.S. EPA considers 24-hour levels of $PM_{2.5}$ between 35-55 μg/m^3 as unhealthy for sensible populations, and between 55-150 μg/m^3 as unhealthy for the general public. Above that concentrations, $PM_{2.5}$ becomes very unhealthy or even hazardous (U.S. EPA, 2012).

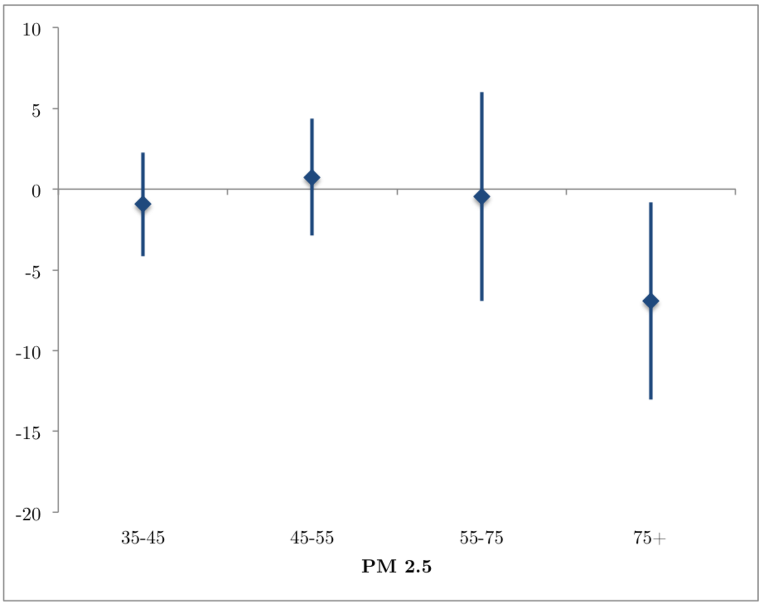
[41]The model does not include leisure. However, the results including a labor-leisure trade-off are identical.

[42]Results are similar using other homothetic functions.

Figure 4: Non-linear effects of $PM_{2.5}$ on hours worked



(a) Households with susceptible individuals



(b) Households without susceptible individuals

Notes: Diamonds represent estimates of β_k, vertical lines are 95% confidence intervals. Omitted category is PM 2.5 below 35 $\mu g/m^3$.

supply, is obtained by solving the following problem:

$$\begin{aligned}
\max_{h_i, L_i} \quad & U(c) \\
\text{subject to} \quad & L_i + h_i = 1, \\
& c = w_1 L_1 + w_2 L_2, \\
& f(h_1, h_2) \geq s.
\end{aligned}$$

Using standard methods, we obtain that $h_1 = sk^{\rho-1}$ and $h_2 = sk^{\rho}$ where $k = \frac{w_1}{w_2}\frac{1-\rho}{\rho}$.

In this framework, pollution affects household's decisions by affecting dependents' health and increasing minimum caregiving needs, s. It is easy to show that if $k = 1$ the effects of pollution on domestic work and labor supply, $\frac{dh_i}{ds}$ and $\frac{dL_i}{ds}$ respectively, are the same for both individuals. However, if $k > 1$, then $\frac{dh_2}{ds} > \frac{dh_1}{ds} > 0$. This implies, that the labor supply of individual 2 drops *more* than for individual 1. Condition $k > 1$ can happen if individual 1 earns a higher wage, $w_1 > w_2$, or if individual 2 has an advantage in providing caregiving, $\rho < 1/2$.

This result suggests that, in the presence of heterogeneous earning opportunities or caregiving ability, households can reduce the negative shock of pollution by re-allocating domestic work across its members. There are several implications of intra-household substitution of hours worked in response to air pollution shocks. First, as the response of different members of the household to air pollution could go in different directions, the overall effect would mask costly substitution (e.g. the cost of lost leisure) and thus understate the cost of air pollution. Second, this substitution would likely result in heterogeneous responses of labor supply to air pollution as stemming from differences in the substitutability of labor.

To examine this possible margin of adjustment, we estimate the baseline model (1) adding interactions of $PM2.5$ with several factors associated with wage differentials such as age, gender, education, role as head of household, or being an independent worker.[43] Similarly to the baseline results, we split the sample between individuals in households with and without susceptible dependents.

We find, however, no evidence of significant heterogeneous effects of pollution driven by these characteristics (see columns 1 and 4 of Table 5). One interpretation is that other constraints

[43] We check that these variables are indeed significantly correlated with differences in earnings. These results are available upon request.

preclude using within-household reallocation of caregiving and labor as a way to attenuate this shock. An alternative explanation is that households might have other, more effective, attenuation strategies.[44] We indirectly examine this alternative explanation by studying the effect of pollution on earnings.

To do so, we estimate the baseline regression (1) using the log of monthly earnings as our outcome. Note that, in contrast to labor outcomes, the period of reference for earnings is the 4 weeks prior to the interview (i.e., weeks t to $t-3$). Thus the reference period for our measure of exposure to $PM_{2.5}$ is weeks $t-1$ to $t-4$. Given the length of the period, using average $PM_{2.5}$ would mask episodes of high pollution. For that reason, we use instead the share of weeks in the reference period in which average $PM_{2.5}$ exceeded the U.S. 24-hour standard. We also use month instead of week fixed effects, and, in some specifications, relax the model by using municipality plus year fixed effects instead of municipality-by-year fixed effects.

Table 5 presents the results (columns 2, 3, 5 and 6). We find that consistent with imperfect attenuation, $PM_{2.5}$ is associated with a (marginally) significant reduction in earnings. Similar to the main results on hours worked, we find that this reduction in earnings occurs mainly in households with susceptible individuals.[45]

[44]For example, households could reallocate leisure over time, i.e, recovering lost working hours in the future, or use sick or vacation days.

[45]We also estimate the results in this section by averaging earnings across household members or adding hours worked. Results are similar, although less precise as this further reduces the number of observations (Appendix Tables B.6 andB.7).

Table 5: Exploring attenuation behavior

	Hours worked	ln(earnings in last month)		Hours worked	ln(earnings in last month)	
	(1)	(2)	(3)	(4)	(5)	(6)
Air pollution	-0.219*	-0.152*	-0.135	-0.111	-0.009	-0.093
	(0.109)	(0.088)	(0.111)	(0.104)	(0.068)	(0.092)
Air pollution × is household head	0.072			-0.011		
	(0.067)			(0.053)		
Air pollution × is female	0.056			-0.003		
	(0.066)			(0.063)		
Air pollution × under 25 years	0.045			0.004		
	(0.096)			(0.077)		
Air pollution × complete secondary	-0.045			0.042		
	(0.068)			(0.072)		
Air pollution × independent worker	0.012			0.131		
	(0.083)			(0.078)		
Measure of air pollution	PM 2.5	% weeks PM 2.5 above 35 μg/m^3		PM 2.5	% weeks PM 2.5 above 35 μg/m^3	
Household has susceptible individuals	yes	yes	yes	no	no	no
Municipality-by-year FE	yes	no	yes	yes	no	yes
Observations	2,167	2,274	2,274	3,051	3,240	3,240
R-squared	0.432	0.600	0.620	0.451	0.625	0.641

Notes: Robust standard errors in parentheses. Standard errors are clustered at the municipality level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions include household fixed effects and the same individual and household controls as the baseline specification (see notes of Table 2). Columns 1 and 4 include household, week and municipality-by-year fixed effects. Columns 2 and 5 include month and municipality fixed while columns 3 and 6 include month and municipality-by-year fixed effects. Columns 1 and 4 also add interactions of measure of air pollution with indicators of being a household head, female, under 25 years of age, or an independent worker. Similar to the baseline regression, PM 2.5 refers to average $PM_{2.5}$ in week $t-1$, where t is the week of reference of labor outcomes. Reference period for earnings is weeks t to $t-3$. In earnings regressions, the reference period for explanatory variable "% weeks PM 2.5 above 35 μg/m^3" is weeks $t-1$ to $t-4$.

5 Conclusion

This paper examines the short-term effect of fine particulate matter on labor supply. This issue is important to assess the social cost of pollution and to inform the design of environmental policies.

Using the case of Lima, Peru, we find evidence of a significant and sizable negative effect. The effects are non linear and heterogeneous, affecting mostly individuals in households with small children and elderly adults.

Our findings shed light on the mechanisms linking pollution to labor supply. They suggest that, at moderate levels, caregiving is an important mechanism linking pollution to labor supply. However, at higher levels, pollution affects all individuals suggesting that, at these levels, the mechanism may be more direct: deterioration of workers' health.

Importantly, our results also point out two important issues not discussed before. First, pollution can have redistributional effects. In our case, the brunt of the pollution externality, in terms of lower labor supply and earnings, is borne by households with small children and elderly adults. This group is also likely to suffer more in terms of poor health. Second, households seem to have a limited ability to reduce the negative effect of this shock on their income by reallocating hours of work to other members of the household.

There are, however, some important issues not addressed in this paper. First, while we examine the short-term effects of pollution we are unable to study possible long-term, cumulative, effects. Second, we do not estimate the effect on other outcomes that may affect household livelihood such as labor productivity, medical expenses, or school absenteeism. Previous studies suggest these are also relevant externalities. Exploring these issues warrants further research.

References

Adhvaryu, Achyuta, Namrata Kala, and Anant Nyshadham, "Management and Shocks to Worker Productivity: Evidence from Air Pollution Exposure in an Indian Garment Factory," mimeo 2014.

Almond, Douglas, Lena Edlund, and Mårten Palme, "Chernobyl's Subclinical Legacy: Prenatal Exposure to Radioactive Fallout and School Outcomes in Sweden," *The Quarterly Journal of Economics*, 2009, *124* (4), 1729–1772.

Aranda, Evelyn, "Senamhi iniciará difusión del pronóstico de calidad del aire este viernes," RPP Noticias, retrieved on 30 December 2015 from `http://rpp.pe/lima/actualidad/senamhi-iniciara-difusion-del-pronostico-de-calidad-del-aire-este-viernes-noticia-4269` 2011.

Beckett, K Paul, PH Freer-Smith, and Gail Taylor, "Particulate pollution capture by urban trees: effect of species and windspeed," *Global Change Biology*, 2000, *6* (8), 995–1003.

Bell, Michelle L, Jonathan M Samet, and Francesca Dominici, "Time-series studies of particulate matter," *Annual Review of Public Health*, 2004, *25*, 247–280.

Chang, Tom, Joshua Graff-Zivin, Tal Gross, and Matthew Neidell, "Particulate Pollution and the Productivity of Pear Packers," NBER Working Paper w19944, 2014.

Chay, Kenneth Y and Michael Greenstone, "The Impact of Air Pollution on Infant Mortality: Evidence from Geographic Variation in Pollution Shocks Induced by a Recession," *The Quarterly Journal of Economics*, 2003, *118* (3), 1121–1167.

CONAM, "Inventario de Emisiones Totales," Lima: Comisión Nacional del Ambiente (CONAM), 2001.

Conley, Timothy G, "GMM estimation with cross sectional dependence," *Journal of Econometrics*, 1999, *92* (1), 1–45.

Currie, Janet and Matthew Neidell, "Air Pollution and Infant Health: What Can We Learn from California's Recent Experience?," *The Quarterly Journal of Economics*, 2005, pp. 1003–1030.

——, **Eric A Hanushek, E Megan Kahn, Matthew Neidell, and Steven G Rivkin**, "Does pollution increase school absences?," *The Review of Economics and Statistics*, 2009, *91* (4), 682–694.

——, **Joshua Graff Zivin, Jamie Mullins, and Matthew Neidell**, "What Do We Know About Short-and Long-Term Effects of Early-Life Exposure to Pollution?," *Annual Review of Resource Economics*, 2014, *6* (1), 217–247.

——, **Matthew Neidell, and Johannes F Schmieder**, "Air pollution and infant health: Lessons from New Jersey," *Journal of Health Economics*, 2009, *28* (3), 688–703.

Deschenes, Olivier, Michael Greenstone, and Joseph S Shapiro, "Defensive investments and the demand for air quality: Evidence from the nox budget program and ozone reductions," NBER Working Paper No. 18267 2012.

DIGESA, "Estudio de saturación Lima Metropolitana y Callao Año 2011," Dirección General de Salud Ambiental (DIGESA), Ministerio de Salud, retrieved on 30 December 2015 from `http://www.digesa.minsa.gob.pe/depa/informes_tecnicos/Estudio%20de%20Saturacion%202012.pdf`. 2012.

Fetzer, Thiemo, "Can Workfare Programs Moderate Violence? Evidence from India," Technical Report, STICERD, LSE 2014.

Gilliland, Frank D, Kiros Berhane, Edward B Rappaport, Duncan C Thomas, Edward Avol, W James Gauderman, Stephanie J London, Helene G Margolis, Rob McConnell, and K Talat Islam, "The Effects of Ambient Air Pollution on School Absenteeism Due to Respiratory Illnesses," *Epidemiology*, 2001, pp. 43–54.

Hanna, Rema and Paulina Oliva, "The effect of pollution on labor supply: Evidence from a natural experiment in Mexico City," *Journal of Public Economics*, 2015, *122*, 68–79.

Hausman, Jerry A, Bart D Ostro, and David A Wise, "Air pollution and lost work," National Bureau of Economic Research, 1984.

Hien, PD, VT Bac, HC Tham, DD Nhan, and LD Vinh, "Influence of meteorological conditions on $PM_{2.5}$ and $PM_{2.5-10}$ concentrations during the monsoon season in Hanoi, Vietnam," *Atmospheric Environment*, 2002, *36* (21), 3473–3484.

Hsiang, Solomon M, "Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America," *Proceedings of the National Academy of Sciences*, 2010, *107* (35), 15367–15372.

Janhäll, Sara, "Review on urban vegetation and particle air pollution–Deposition and dispersion," *Atmospheric Environment*, 2015, *105*, 130–137.

Jayachandran, Seema, "Air quality and early-life mortality evidence from Indonesias wildfires," *Journal of Human Resources*, 2009, *44* (4), 916–954.

Lavy, Victor, Avraham Ebenstein, and Sefi Roth, "The Long Run Economic Consequences of High-Stakes Examinations: Evidence from Transitory Variation in Pollution," *American Economic Journal: Applied Economics*, forthcoming.

Li, Teng, Haoming Liu, and Alberto Salvo, "Severe Air Pollution and Labor Productivity," IZA Discussion Paper No. 8916 2015.

Lleras-Muney, Adriana, "The needs of the army using compulsory relocation in the military to estimate the effect of air pollutants on childrens health," *Journal of Human Resources*, 2010, *45* (3), 549–590.

Ostro, Bart D, "The effects of air pollution on work loss and morbidity," *Journal of Environmental Economics and Management*, 1983, *10* (4), 371–382.

Park, Hyesook, Boeun Lee, Eun-Hee Ha, Jong-Tae Lee, Ho Kim, and Yun-Chul Hong, "Association of air pollution with school absenteeism due to illness," *Archives of pediatrics & adolescent medicine*, 2002, *156* (12), 1235–1239.

Pope III, C. Arden and Douglas W. Dockery, "Health effects of fine particulate air pollution: lines that connect," *Journal of the Air & Waste Management Association*, 2006, *56* (6), 709–742.

Ransom, Michael R and C Arden Pope, "Elementary school absences and PM_{10} pollution in Utah Valley," *Environmental Research*, 1992, *58* (1), 204–219.

Sánchez-Ccoyllo, O. R., C. G. Ordoñez, M. E. Gavidia, J. S. Silva, J. L. Angulo, D. R. Blas, J. E. Chávez, R. R. Aliaga, A. Zevallos, J. C. Canales, and A.R Aguirre, "Evaluación de la calidad del aire en Lima Metropolitana 2011," Lima: SENAMHI, retrieved on 30 December 2015 from `http://www.senamhi.gob.pe/usr/dgia/pdf_dgia_eval2011.pdf`. 2013.

Sanders, Nicholas J, "What doesnt kill you makes you weaker prenatal pollution exposure and educational outcomes," *Journal of Human Resources*, 2012, *47* (3), 826–850.

Thatcher, Tracy L and David W Layton, "Deposition, resuspension, and penetration of particles within a residence," *Atmospheric Environment*, 1995, *29* (13), 1487–1497.

U.S. EPA, "Final Report: Integrated science assessment for particulate matter," U.S. Environmental Protection Agency (EPA). Washington, DC, 2009.

——, "Revised air quality standards for particle pollution and updates to the Air Quality Index (AQI)," U.S. Environmental Protection Agency (EPA), retrieved on 7 January 2016 from `http://www3.epa.gov/airquality/particlepollution/2012/decfsstandards.pdf`. 2012.

Vecchi, R, G Marcazzan, G Valli, M Ceriani, and C Antoniazzi, "The role of atmospheric dispersion in the seasonal variation of PM_1 and $PM_{2.5}$ concentration and composition in the urban area of Milan (Italy)," *Atmospheric Environment*, 2004, *38* (27), 4437–4446.

Verbeek, Marno and Theo Nijman, "Testing for selectivity bias in panel data models," *International Economic Review*, 1992, pp. 681–703.

Vette, Alan F, Anne W Rea, Philip A Lawless, Charles E Rodes, Gary Evans, V Ross Highsmith, and Linda Sheldon, "Characterization of indoor-outdoor aerosol concentration relationships during the Fresno PM exposure studies," *Aerosol Science & Technology*, 2001, *34* (1), 118–126.

Wilson, J Gaines, Simon Kingham, Jamie Pearce, and Andrew P Sturman, "A review of intraurban variations in particulate air pollution: Implications for epidemiological research," *Atmospheric Environment*, 2005, *39* (34), 6444–6462.

Wooldridge, Jeffrey M., *Econometric analysis of cross section an panel data*, Cambridge, MA: MIT Press, 2002.

Wooldridge, Jeffrey M, "Fixed-effects and related estimators for correlated random-coefficient and treatment-effect panel data models," *Review of Economics and Statistics*, 2005, *87* (2), 385–390.

Zivin, Joshua Graff and Matthew Neidell, "The Impact of Pollution on Worker Productivity," *American Economic Review*, 2012, *102* (7), 3652–73.

—— **and** ——, "Environment, Health, and Human Capital," *Journal of Economic Literature*, 2013, *51* (3), 689–730.

Zweig, Jacqueline S., John C. Ham, and Edward L. Avol, "Pollution, Test Scores and Distribution of Academic Achievement: Evidence from California Schools 2002-2008," 2014.

APPENDIX

A Additional figures

Figure A.1: Distribution of weekly average PM_{10} (in $\mu g/m^3$), years 2007-2011

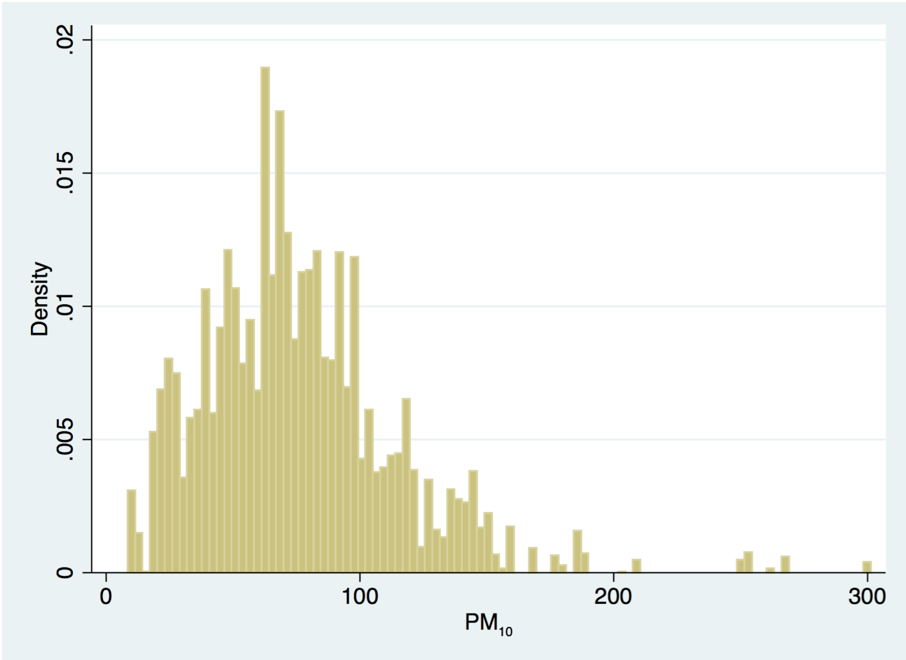


Figure A.2: Distribution of weekly average NO_2 (in $\mu g/m^3$), years 2007-2011

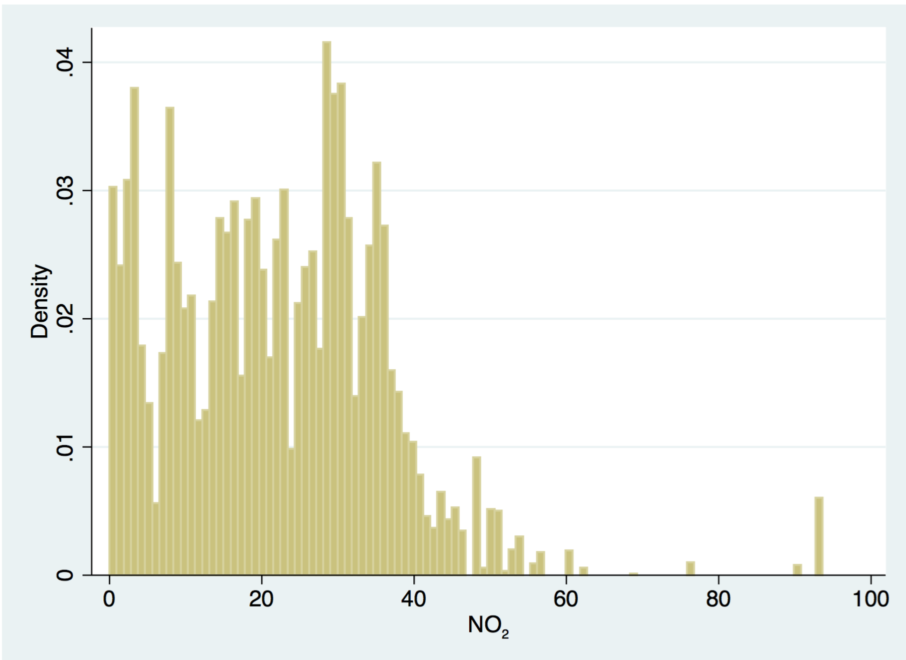


Figure A.3: Distribution of weekly average SO_2 (in $\mu g/m^3$), years 2007-2011

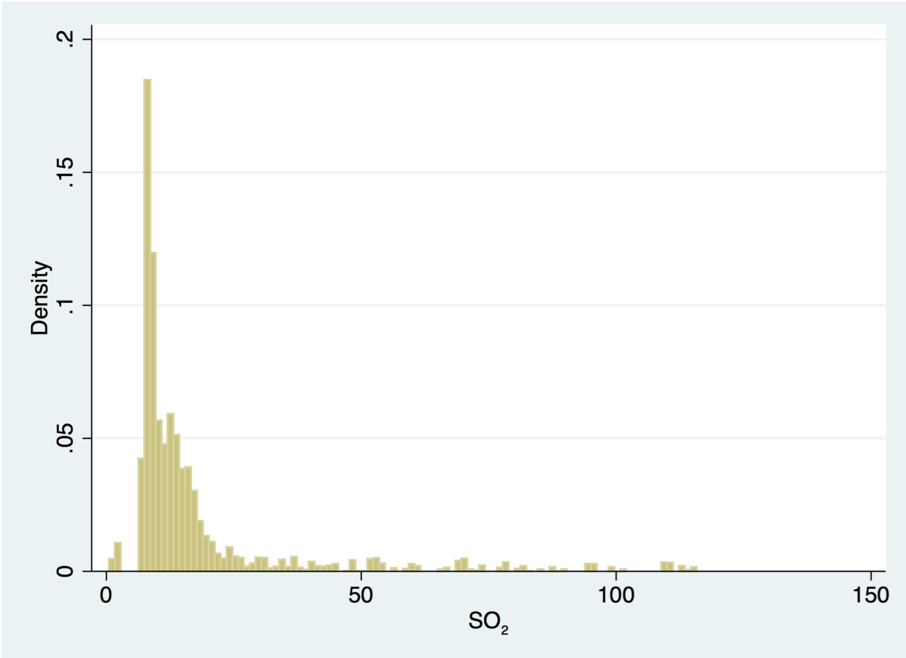
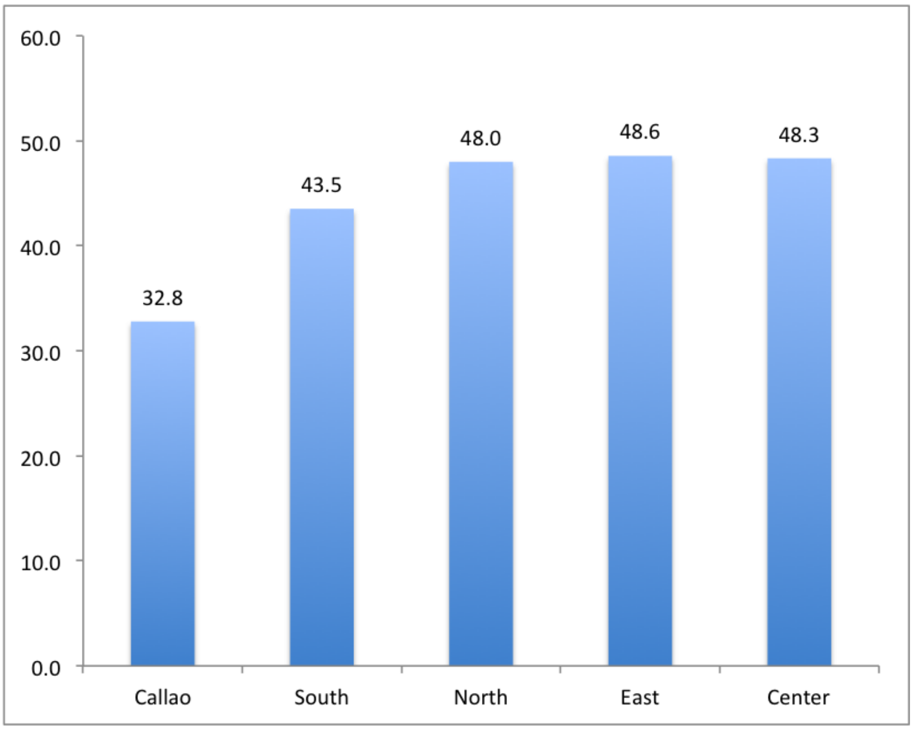


Figure A.4: Average $PM_{2.5}$ (in $\mu g/m^3$), years 2007-2011, by monitoring station



B Additional tables

Table B.1: Mean of children's health indicators

Variable	Mean
$PM_{2.5}$	53.9
$PM_{2.5} > 35\ \mu g/m^3$ (%)	83.8
Has cough and short breath (%)	19.9
Has fever (%)	22.4
Has diarrhea (%)	12.3
Has anemia (%)	32.1
Nr. observations	712

Notes: Reference period for morbidity variables is weeks $t-1$ and $t-2$, where t is the date of survey. Reference period for measures of pollution is weeks $t-2$ and $t-3$.

Table B.2: Non-linear relation of $PM_{2.5}$ and children's health

	Cough and short breath	Fever	Diarrhea	Anemia
PM 2.5 between	0.061	0.080	0.025	0.045
35-45 μg/m^3	(0.061)	(0.065)	(0.042)	(0.087)
PM 2.5 between	0.101*	-0.005	0.046	-0.026
45-55 μg/m^3	(0.055)	(0.062)	(0.045)	(0.079)
PM 2.5 between	0.144**	-0.001	0.030	0.040
55-75 μg/m^3	(0.058)	(0.065)	(0.042)	(0.091)
PM 2.5 above	0.078	0.074	-0.010	-0.071
75 μg/m^3	(0.060)	(0.069)	(0.050)	(0.094)
Observations	712	712	712	492
R-squared	0.057	0.065	0.069	0.244

Notes: Robust standard errors in parentheses. Standard errors are clustered at the survey block level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions are estimated using OLS and include the same control variables as in Table 3. The omitted category is PM 2.5 lower than 35 μg/m^3.

Table B.3: Heterogeneous effects of $PM_{2.5}$ on hours worked

	Hours worked			
	(1)	(2)	(3)	(4)
Air pollution	-0.039	-0.043	-0.107	2.317
	(0.050)	(0.110)	(1.637)	(4.187)
Air pollution × household has susceptible individuals	-0.153**	-0.160*	-6.711**	-7.204**
	(0.074)	(0.083)	(2.912)	(3.369)
Air pollution × household is poor		0.072		2.145
		(0.070)		(3.827)
Air pollution × age		0.001		-0.082
		(0.002)		(0.092)
Air pollution × number of income earners		-0.008		0.175
		(0.026)		(0.677)
Measure of air pollution	PM 2.5		PM 2.5 above 35 μg/m^3	
Observations	5,218	5,218	5,218	5,218
R-squared	0.440	0.440	0.440	0.440

Notes: Robust standard errors in parentheses. Standard errors are clustered at the municipality level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. Regressions include the same controls as the baseline specification (see notes of Table 2 plus full interactions with an indicator of a household having a susceptible individual. Columns 2 and 4 also add interactions of air pollution with an indicator for poor household, individual's age, and number of income earners. Columns 1 and 2 use PM 2.5 as measure of air pollution, while columns 3 and 4 use an indicator of PM 2.5 exceeding the U.S. standard.

Table B.4: Testing for attrition bias

	Hours worked			
	(1)	(2)	(3)	(4)
Drops from sample next year	-2.812	2.814	-3.206	2.799
	(2.122)	(2.537)	(2.309)	(2.571)
PM 2.5	-0.194***	-0.040		
	(0.045)	(0.048)		
PM 2.5 above 35 μg/m^3			-7.081***	-0.199
			(2.390)	(1.576)
Household has susceptible individuals	Yes	No	Yes	No
Observations	2,167	3,049	2,167	3,049
R-squared	0.430	0.446	0.429	0.446

Notes: Robust standard errors in parentheses. Standard errors are clustered at the municipality level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. Regressions include the same controls as the baseline specification (see notes of Table 2. "Drops from sample next year" is an indicator equal to 1 if household drops from panel sample the following year, and 0 otherwise.

Table B.5: Non-linear effect of $PM_{2.5}$ on hours worked

	Hours worked		p-value H_0: (1)=(2)
	(1)	(2)	(3)
PM 2.5 between 35-45 $\mu g/m^3$	-4.940*	-0.944	0.168
	(2.758)	(1.585)	
PM 2.5 between 45-55 $\mu g/m^3$	-7.318**	0.737	0.047
	(2.801)	(1.782)	
PM 2.5 between 55-75 $\mu g/m^3$	-9.685***	-0.445	0.081
	(3.090)	(3.175)	
PM 2.5 above $\mu g/m^3$	-10.635***	-6.941**	0.439
	(3.036)	(3.001)	
Household has susceptible individual	Yes	No	
Observations	2,167	3,051	
R-squared	0.430	0.448	

Notes: Robust standard errors in parentheses. Standard errors are clustered at the municipality level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions include the same controls as the baseline specification (see notes of Table 2. The omitted category is PM 2.5 lower than 35 $\mu g/m^3$. Column 3 reports the p-value of a test that the estimates in column 1 and 2 are the same. This is obtained from estimating equation (2) and including full interactions with dummies of the household having a susceptible individual. The p-values correspond to the estimated interaction terms.

Table B.6: $PM_{2.5}$ and average household earnings

	ln(average household earnings)					
	(1)	(2)	(3)	(4)	(5)	(6)
% weeks PM 2.5	-0.206*	-0.135	-0.082	0.011	0.008	-0.016
above 35 μg/m^3	(0.102)	(0.151)	(0.172)	(0.046)	(0.072)	(0.113)
Household F.E.	No	Yes	Yes	No	Yes	Yes
Municipality-by-year FE	No	No	Yes	No	No	Yes
Household has susceptible individuals	Yes	Yes	Yes	No	No	Yes
Observations	1,122	1,122	1,122	1,716	1,716	1,716
R-squared	0.304	0.815	0.858	0.337	0.822	0.847

Notes: Robust standard errors in parentheses. Standard errors are clustered at the municipality level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. Regressions use observations aggregated at the household level by taking the average of income earners, and are estimated using a panel data model with fixed effects and no sample weights. All regressions include municipality, month and year fixed effects, average temperate and humidity, and characteristics of the average income earner: age, age^2, schooling, schooling^2, share of females, share of earners having a second job, and share of independent workers. Columns 2 and 4 add household fixed effects, while columns 3 and 6 also add municipality-by-year fixed effects. Reference period for household earnings is weeks t to $t-3$. Reference period for explanatory variable "% weeks PM 2.5 above 35 μg/m^3" is weeks $t-1$ to $t-4$.

Table B.7: $PM_{2.5}$ and total hours worked by household members

	Total hours worked	
	(1)	(2)
PM 2.5	-0.203*	-0.076
	(0.105)	(0.135)
Household has susceptible individuals	Yes	No
Observations	984	1,480
R-squared	0.671	0.605

Notes: Robust standard errors in parentheses. Standard errors are clustered at the municipality level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. Regressions use observations aggregated at the household level, and are estimated using a panel data model with fixed effects and no sample weights. The outcome "total hours worked" is the sum of hours worked by all household members. All regressions include household, municipality-by-year, and week fixed effects, average temperate and humidity, share of females, share of workers having a second job, share of independent workers and characteristics of the average worker: age, age^2, schooling, and schooling^2.

C Ancillary results

This section presents additional results of the effect of pollution on labor supply.

Table C.1 examines the effect of $PM_{2.5}$ on measures of the extensive margin of labor supply, such as labor force participation, employment rate, or likelihood of having a second job. There is, however, no significant reduction in any of these indicators. These results suggest that the main short-term effect of pollution seems to be on the intensive margin of labor supply, i.e., hours worked.

Table C.2 examines the effect on hours worked of other air pollutants, such as PM_{10}, SO_2, and NO_2. These air pollutants are highly, but not perfectly, correlated to $PM_{2.5}$ (see table C.3). Our preferred specifications (columns 1 to 6) include only one measure of air pollutant at the time, while columns 7 and 8 includes all of them. These last regressions may be less precise due to multicollinearity.

Similar to the results using fine particulate matter ($PM_{2.5}$) we find a negative relationship between hours worked and air pollutants. The magnitude is larger for individuals in households with susceptible dependents. However, except in the case of NO_2, the estimates are not statistically significant. This result may be due to $PM_{2.5}$ effectively being more harmful than other pollutans. For example, U.S. EPA (2009) reports that there is causal evidence linking $PM_{2.5}$ to health problems, but the evidence is less conclusive for other air pollutants. We cannot, however, reject the possibility that this insignificant result is due to noisy data and lack of statistical power.

Table C.1: Effect of $PM_2.5$ on indicators of extensive margin of labor supply

	Labor force (1)	Employed (2)	Has second job (3)
A. Households with susceptible individuals			
PM 2.5	-0.000	0.001	-0.000
	(0.001)	(0.001)	(0.001)
Observations	3,163	2,349	2,170
R-squared	0.413	0.376	0.376
B. Households without susceptible individuals			
PM 2.5	-0.000	0.001***	0.001
	(0.001)	(0.000)	(0.001)
Observations	4,515	3,346	3,055
R-squared	0.488	0.377	0.364

Notes: Robust standard errors in parentheses. Standard errors are clustered at the municipality level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions are estimated using OLS and include household, week, and municipality-by-year fixed effects, characteristics of individual (gender, age, age^2, schooling, $schooling^2$, type of household member), and monthly temperature and humidity. Column 1 uses the sample of individuals of working age (14-65 years). Column 2 uses the sample of indviduals in the labor force. Column 3 uses the sample of employed individuals. PM 2.5 is average $PM_{2.5}$ in week $t-1$, where t is the reference week for labor outcomes.

Table C.2: Effect of other air pollutants on hours worked

	Hours worked							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PM_{10}	-0.042	0.002					-0.031	0.012
	(0.043)	(0.024)					(0.065)	(0.034)
NO_2			-0.095**	-0.009			0.030	0.029
			(0.040)	(0.051)			(0.097)	(0.063)
SO_2					-0.045	-0.008	0.069	-0.029
					(0.032)	(0.039)	(0.089)	(0.076)
$PM_{2.5}$							-0.124	-0.041
							(0.111)	(0.043)
Household has suscept. indiv.	Yes	No	Yes	No	Yes	No	Yes	No
Observations	2,084	2,981	2,337	3,326	2,412	3,441	1,637	2,390
R-squared	0.434	0.446	0.422	0.443	0.416	0.432	0.464	0.480

Notes: Robust standard errors in parentheses. Standard errors are clustered at the municipality level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions include the same controls as the baseline specification (see notes of Table 2). Similarly, the measures of air pollution (PM_{10}, NO_2, SO_2 and $PM_{2.5}$) are the average in week $t-1$, where t is the reference week for labor outcomes.

Table C.3: Correlation matrix of main air pollutants

	$PM_{2.5}$	PM_{10}	NO_2	SO_2
$PM_{2.5}$	1			
PM_{10}	0.4698	1		
NO_2	0.2969	0.2441	1	
SO_2	0.2771	0.201	0.0173	1