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# Particulate matter and labor supply: The role of caregiving and non-linearities[☆]

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Abstract

This paper examines the effect of air pollution on labor supply in Lima, Peru.
We focus on fine particulate matter ($PM_{2.5}$), an important pollutant for health according to the medical literature, and show that moderate levels of pollution reduce hours worked for working adults. Our research design takes advantage of rich household panel data in labor out-comes to address omitted variables. This research design allows us to investigate whether the response to air pollution is non-linear. We find that the effect of moderate pollution levels on hours worked is concentrated among households with susceptible dependents, i.e., small children and elderly adults; while the highest concentrations affect all house-holds. This suggests that caregiving is likely a mechanism linking air pollution to labor supply at moderate levels. We provide further evidence of this mechanism using data on children morbidity. Finally, we find no evidence of intra-household attenuation behavior. For instance, there is no re-allocation of labor across household members, and earnings decrease with air pollution.

## 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.

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[1] For a review of this literature see Currie et al. (2014) or Graff-Zivin and Matthew (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., 2016), and to increases in school absenteeism (Ransom and Pope, 1992; Gilliland et al., 2001; Park et al., 2002; Currie et al., 2009).

[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).

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 the 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]

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 levels, 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 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 reallocation 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.

## Background

### *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 μm in diameter.[5] It can be produced by natural sources,

[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., 2009, 2009), and ozone (Lleras-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. (2016) and Li et al. (2015).

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

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

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 and Douglas, 2006).[6]

A large medical literature finds evidence of a causal effect of short term exposure to $PM_{2.5}$ 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). 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, 0–1 days, for cardiovascular diseases and for elderly patients with other diseases, and larger lags, 3-5 days, for asthma hospital admissions.

### *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 $\mu g/m^3$. This level is above the U.S. 24-h standard of 35 $\mu g/m^3$ 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 Fig. 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 Fig. 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 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 Fig. 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.

## Methods

### *Data*

**Labor and health data** We use micro-data from the Peruvian National Household survey (ENAHO). This survey covers years 2007–2011 and includes geographical coordinates of households' residences at the level of census block. The ENAHO is a rolling survey and 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]

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

[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 Figs. 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 $PM_{2.5}$.

[10] See Fig. 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.

[13] The panel sample is unbalanced. Households enter the sample in different years, not only at the beginning; and by design 20% of the sample is renewed every year. The majority of households are observed only two years (n = 586) or three years (n = 180). Note that while the ENAHO is representative

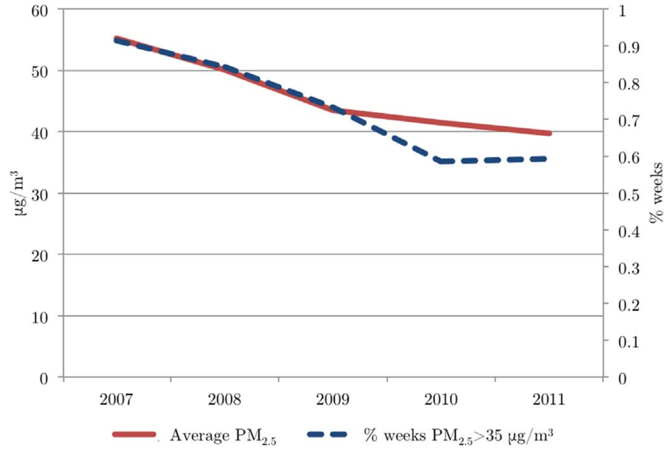


**Fig. 1.** Evolution of $PM_{2.5}$, years 2007–2011.

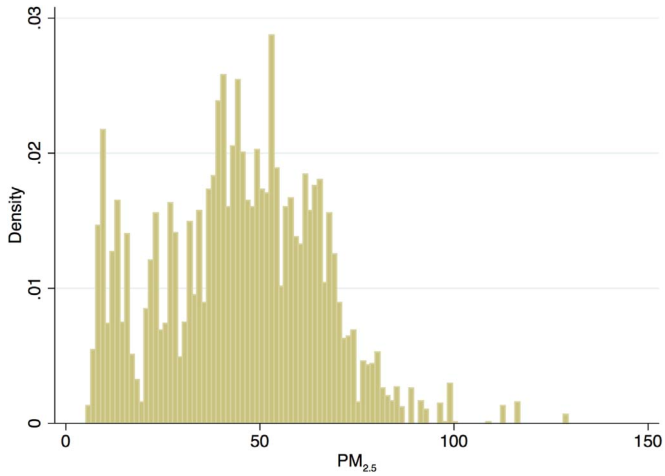


**Fig. 2.** Distribution of weekly average $PM_{2.5}$ (in μg/m$^3$), years 2007–2011.

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.[15] 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 in our baseline regression.

To obtain measures of health, we use the Demographic and Health Survey (DHS) for 2007–2009.[16] We use the reported coordinates of each household's residence as a proxy for its location. Note that these coordinates are randomly displaced by up to 3 km. This increases the measurement error in our pollution variable. 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. We have, however, no comparable data on workers or elderly adults' health. Due to this data limitation we can only explore the effects of pollution on child's health.[17]

**Pollution data** We obtain daily measures of key pollutants such as $PM_{2.5}$, $PM_{10}$, nitrogen dioxide ($NO_2$) and sulphur dioxide ($SO_2$) for years 2007–2011. These measures provide average levels of pollutants for a 24 h-period and were collected every 2–3 days each week.[18]

(*footnote continued*)
of Lima city, the panel sample is not. Furthermore, as discussed below, we trim the panel sample and drop observations located far away from monitoring stations. For these reasons, results should not be interpreted as estimates for Lima city, but only for the sample used in the study.

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

[15] Results are robust to dropping these observations. Note that the number of unemployed individuals is very low, around 0.2%.

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

[17] The ENAHO survey contains self-reported information on health conditions, such as illnesses or accidents in the last four weeks. However, we do not use this information because it does not distinguish between respiratory and non-respiratory diseases, and has a longer time horizon.

[18] The collection dates in a given week were randomly chosen. The collection process was done by trained personnel of the Ministry of Health using

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 Fig. 3).

Note that these monitoring stations were installed as part of the first project to systematically measure air quality in Peru.[19] 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 $t-1$.[20] Thus, we use exposure to pollutants in the week before labor outcomes are realized. This responds to previous evidence suggesting a lag of a few days between exposure to pollution and health problems. In the case of health outcomes, the reference period for morbidity questions is weeks $t$ and $t-1$ (i.e., the 14 days prior to the interview date). In that case, we use measures of pollution in weeks $t-1$ and $t-2$. 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 km 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.

Fig. 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.

*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 monthly temperature and 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 presence of local labor supply determinants that evolve slowly over time, such as gradual changes in labor markets or differential growth across municipalities. However, it does not control for time-varying omitted variables at higher frequency, like local traffic conditions.[24] 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:

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

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

(*footnote continued*)
active air sampling procedures. The detailed data collection protocol is available at http://www.digesa.sld.pe/norm_consulta/protocolo_calidad_de_aire.pdf.

[19] 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.

[20] We also estimate the baseline regression using different lags and leads (see Fig. A.5 in the Appendix). We find that the only significant effect on households with susceptible individuals is obtained when using $PM_{2.5}$ in week $t-1$. This is consistent with the reported lags of 3–5 days between exposure to pollution and respiratory diseases.

[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] We examine this issue in Section 4.2.

[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.

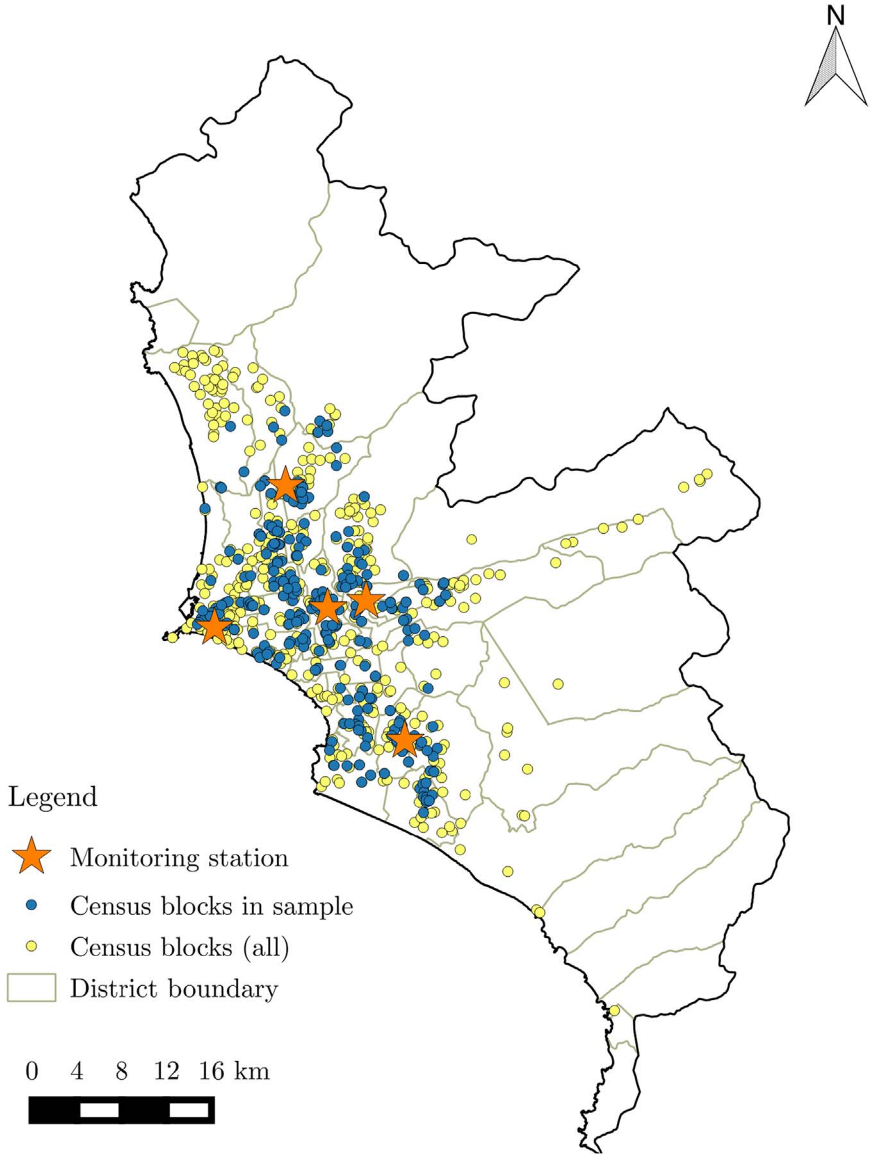


**Fig. 3.** Map of Lima city with monitoring stations and Census blocks. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

the interview date. The main outcome is the number of hours worked, $hours_{ij,t}$. $PM2.5_{j,t-1}$ refers to the measure of fine particulate matter 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 $\mu g/m^3$) or a step function of the average $PM_{2.5}$. Eq. (1) includes week fixed effects, $\eta_t$, to control for seasonality, household fixed effects, $\alpha_j$; and a set of time-varying controls, $\mathbf{X}_{ij,t}$, that includes municipality-by-year fixed effects, weather, and worker's characteristics.[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 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

[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 and alternative clustering approaches (see Table 4 and Appendix Table B.5).

**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 μg/$m^3$ (%) | 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 | 2.4 | 2.6 | 2.4 | 0.000 |
| Household size | 4.3 | 5.2 | 3.7 | 0.000 |
| No. households | 1,244 | 571 | 849 | |
| No. observations | 5,218 | 2,167 | 3,051 | |

*Notes*: $PM_{2.5}$, $PM_{10}$, $SO_2$ and $NO_2$ are measured in μg/$m^3$. 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.

**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) | −0.153 ** | | -6.711 ** | |
| | (0.074) | | (2.912) | |
| 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 *** 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.

DHS coordinates as a proxy for household location and calculate the average $PM_{2.5}$ in weeks $t-2$ and $t-1$. This corresponds to a one-week lag of the reference period for health outcomes. Our regression uses as independent variables an indicator of average $PM_{2.5}$ exceeding the U.S. standard and the log of average $PM_{2.5}$.[38]

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 percentage point reduction in the incidence of acute respiratory diseases. To put this figure in context, note that the average incidence of cough with short breath is 19.9%.

*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, we examine the relationship between *contemporaneous* exposure to pollution and hours 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).[39]

Columns 3–5 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.

Our baseline specification clusters the errors at municipality level (n=35). Municipalities are larger geographical unit than census blocks. This is conservative approach that allows for arbitrary correlation, both over time and between units, within each municipality.[40] In column 6, we also estimate standard errors using the procedure suggested by Conley (1999).[41] This procedure accounts for both serial and spatial correlation among nearby units.

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.4 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 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.6 in the Appendix).

*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

[38] 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.3 in the Appendix).

[39] Results are also insignificant when using average $PM_{2.5}$ in weeks $t+1$ or $t+2$ (See Fig. A.5 in the Appendix.

[40] In addition, we check the robustness of the main results to alternative approaches such as clustering at the level of block-week-year and two-way clustering by block and week-year (see Table B.5 in the Appendix).

[41] We use the STATA ado file *reg2hdfespatial* developed by Fetzer (2014) and based on Hsiang (2010). We use a one year time lag and a distance cut-off of eight kilometers.

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**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 μg/m$^3$ | 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) |
| Mean values | 19.9 | 22.4 | 12.3 | 32.1 |
| 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.

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:

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

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 $k$.[42] Similarly to the baseline results, we split the sample between individuals in households with and without susceptible dependents.

Fig. 4a and b display the estimates of $\beta_k$ for both samples.[43] 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 (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.[44] 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.

*Attenuation behavior*

An important question is whether households attenuate the negative, short-term, impact of air pollution. The previous results suggest that households are unable to fully attenuate the negative effect of pollution on hours worked. However, they could try to reduce the negative impact on income.

A possible strategy would be to reallocate caregiving duties to household members with relatively worse labor opportunities (or a comparative advantage on caregiving). This would attenuate the negative shock on labor supply of main providers, and the associated reduction on earnings.

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

[42] 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.

[43] See Table B.7 in the Appendix for the regression estimates.

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

**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 estimated 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 5 estimates a semi-logarithmic model using ln(PM. 2.5) as dependent variable. Column 6 estimates standard errors using the method proposed by Conley (1999).

household service, namely, care for dependents.[45] 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 $\rho \in (0, 1)$.[46] Household utility, $U(c)$, depends of total consumption, $c$.

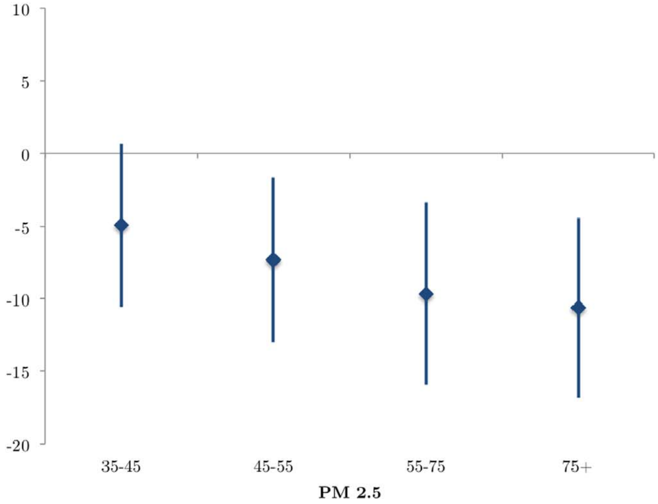
The household's allocation of domestic work, and thus choice of each individuals' labor supply, is obtained by solving the following problem:

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

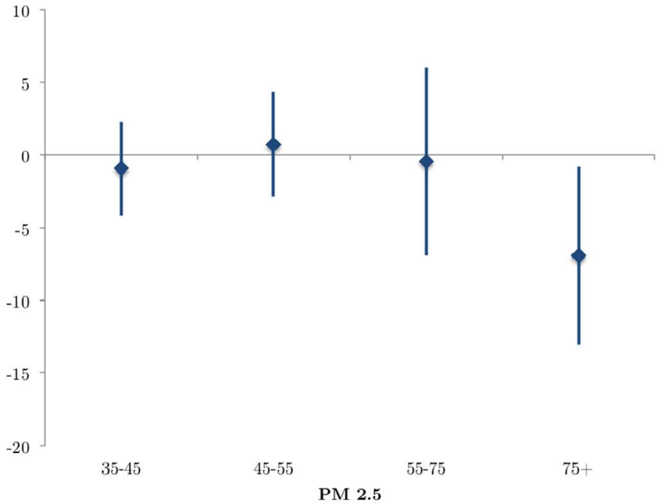
In this framework, pollution affects household's decisions by affecting dependents' health and increasing minimum caregiving needs, $s$. Using standard methods, we obtain that $h_1 = sk^{\rho-1}$ and $h_2 = sk^{\rho}$ where $k \equiv \frac{w_1}{w_2}\frac{1-\rho}{\rho}$. Thus, an increase in pollution would increase domestic work $(h_1, h_2)$ and decrease labor supply of both workers.

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 an increase of air pollution would reduce labor supply of worker 2 *more* than for individual 1.[47] Condition $k > 1$ could happen if individual 1 earns a higher wage,

[45] The model does not include leisure. However, the results including a labor-leisure trade-off are identical.
[46] Results are similar using other homothetic functions.
[47] This results depends on the substitutability of $h_1$ and $h_2$. If both are perfect substitutes the effect is even more evident. In that case, pollution would




(a) Households with susceptible individuals




(b) Households without susceptible individuals

**Fig. 4.** Non-linear effects of $PM_{2.5}$ on hours worked. *Notes*: Diamonds represent estimates of $\beta_k$, vertical lines are 95% confidence intervals. Omitted category is PM 2.5 below 35 μg/m$^3$.

$w_1 > w_2$, or if individual 2 has an advantage in providing caregiving, $\rho < 1/2$.

The model suggests that, in the presence of heterogeneous workers, households could minimize the negative shock of pollution by re-allocating domestic duties, and labor, among its members. This implies that the negative effect of air pollution on hours worked would be *larger* for individuals with relatively lower wages.

To examine this possible attenuation behavior, 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.[48] Similarly to the baseline results, we split the sample between individuals in households with and without susceptible dependents.

Some results are suggestive of heterogeneous effects (see Table 5).[49] For instance, the negative effect of PM2.5 on hours worked is slightly smaller for workers who are household heads or have a job contract. The estimates of these heterogeneous effect are, however, statistically insignificant. One possible interpretation is that other constraints preclude using within-household

(*footnote continued*)
only reduce $L_2$ and have no effect on $L_1$.

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

[49] See Table B.8 in the Appendix for results using the sample of households without susceptible individuals.

**Table 5**
Exploring attenuation behavior.

| | Hours worked | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| PM 2.5 | −0.185 *** (0.039) | −0.190 *** (0.063) | −0.175 *** (0.043) | −0.132* (0.070) | −0.199 *** (0.058) | −0.195 *** (0.042) |
| PM 2.5 × worker characteristic | 0.025 (0.062) | 0.028 (0.068) | −0.004 (0.083) | −0.058 (0.069) | 0.022 (0.084) | 0.062 (0.078) |
| Worker characteristic | Is household head | Is female | Under 25 years | Complete secondary | Indep. worker | Has job contract |
| Household has susceptible indiv. | yes | yes | yes | yes | yes | yes |
| Observations | 2,167 | 2,167 | 2,167 | 2,167 | 2,167 | 2,167 |
| R-squared | 0.422 | 0.422 | 0.422 | 0.423 | 0.430 | 0.422 |

*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, week and municipality-by-year fixed effects, and the same individual and household controls as the baseline specification (see notes of Table 2) plus interactions of PM 2.5 with workers' characteristics. Sample includes only workers in households with susceptible individuals.

reallocation of caregiving as a way to attenuate this shock. For example, there may be a limit on how many hours of work a worker can miss and thus additional caregiving would have to be shared between household members.

An alternative explanation is that households might have other, more effective, attenuation strategies. For example, workers could use their vacation or sick days. In that case, air pollution would reduce hours worked, but have a smaller, or even negligible, effect on income. This strategy would be limited, however, to workers with such job benefits. We indirectly examine this alternative explanation by studying the effect of air pollution on earnings.

To do so, we estimate the baseline regression (1) using the log of monthly earnings as outcome variable. Note that, in contrast to labor outcomes, the period of reference for earnings is the four 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-h standard. We also use month instead of week fixed effects as seasonality controls, and use year fixed effects instead of municipality-by-year fixed effects.[50] For these reasons, the results on earnings are not comparable to the ones obtained on hours worked and should be interpreted with care.

To capture possible heterogeneous effects by access to employee benefits, we distinguish workers with and without job contracts. We consider a worker to have a job contract if she is a dependent worker with an indefinite or fixed-term contract. Only workers with these types of contracts are entitled to paid vacation days, and other employee benefits such as medical insurance and paid sick leave.[51] In the sample, only 30% of workers have a job contract.

Table 6 presents the results. There are three important observations. First, consistent with imperfect attenuation, $PM_{2.5}$ is associated with a (marginally) significant reduction in earnings for the average worker (column 1).[52] Second, the reduction in earnings occurs mainly in households with susceptible individuals. Finally, the reduction in earnings seem to occur mostly among workers *without* job contracts (column 2). In contrast, hours worked drop for both workers with and without contracts.[53]

A possible interpretation of these findings is that households mitigate the short-term negative impact of pollution on income mainly by using employee benefits, such as vacation or sick days, while households without those benefits have limited ability to attenuate this shock. There are, however, alternative explanations that we cannot rule out. For instance, the

[50] Results adding municipality-by-year fixed effects are similar but noisier (see Table B.9 in the Appendix).

[51] Workers without contracts include: independent workers (i.e, self-employed workers and business owners), workers in probationary period, apprentices and trainees, and dependent workers without a contract.

[52] 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 (see Appendix Tables B.10 and B.11).

[53] The estimated effects of PM2.5 on hours worked for both groups are -0.195 and -0.133 respectively (see column 6 in Table 5).

**Table 6**
$PM_{2.5}$ and earnings.

| | ln(earnings in last month) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| A. % weeks PM 2.5 above 35 μg/m$^3$ | −0.152* | −0.195* | −0.009 | 0.009 |
| | (0.088) | (0.113) | (0.068) | (0.078) |
| B. % weeks PM 2.5 above 35 μg/m$^3$ × has job contract | | 0.107 | | −0.045 |
| | | (0.132) | | (0.100) |
| C. p-value $H_0$: $A + B = 0$ | | 0.406 | | 0.685 |
| Household has susceptible individuals | yes | yes | no | no |
| Observations | 2,274 | 2,274 | 3,240 | 3,240 |
| R-squared | 0.600 | 0.603 | 0.625 | 0.631 |

*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, month and year fixed effects, and the same individual and household controls as the baseline specification (see notes of Table 2). The reference period for explanatory variable % weeks PM 2.5 above 35 μg/m$^3$ is weeks $t-1$ to $t-4$. Row C displays the p-value of the test $A + B = 0$, where A and B refer to the estimates in first two rows.

lack of effect on earnings may be due to short-term contractual wage rigidities, or lack of statistical power.[54]

## 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 lower earnings, is borne by households with small children and elderly adults, and informal workers. Second, households seem to have a limited ability to reduce the negative effect of this shock on their income by reallocating caregiving duties among 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.

## Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.jeem.2017.02.008.

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[54] In addition note that we cannot observe wages or output per worker, and thus cannot explore presence of productivity effects as in Graff-Zivin and Neidell (2012) and Chang et al. (2014).

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