The unequal effect of pollution exposure on labour supply across gender

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Abstract

This paper studies the effects of air pollution on labour supply by gender in Mexico City. We differentiate between the health, income and policy effect. We use a regression discontinuity design to identify the policy effect of the "Environmental Contingency Program" and labour supply decisions in pre- and post-contingency periods. Further, we supplement this evidence with information on pollution from measurement stations across the city linked to a city-representative labour force survey. We find evidence that contemporaneous pollution exposure at moderate levels reduce labour supply, whilst there are dramatic reductions at high levels of pollution with heterogeneous effects by formality status. Moreover, pollution seems to decrease working hours even in non-emergency times with differential effects by gender. For male workers the income effect dominates, and thus labour supply increases at high levels of pollution. Moreover, at the extensive margins, informal male workers appear to be the least able to drop-out of employment in high-pollution days. The story is though different at the intensive margins. Where most female and formal workers are able to reduce their hours of work, informal female workers may have no alternatives. Female informal workers have the highest increase in minutes of work during the peak pollution days.

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1 Introduction

A recent report from the World Health Organization considers air pollution as the largest environmental risk factor globally. The data from the global network of monitoring stations shows that only 16% of the assessed population in big cities around the world is exposed to levels that are complying with WHO air quality guidelines (World Health Organization, 2016). This level of exposure is associated with 3 million excess deaths per year (Vos et al., 2020).

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Ambient air pollution has been rising over the past 15 years and thus have the associated economic and social cost (Roy and Braathen, 2017). Estimates of the economic loss are around 6 percent of global GDP for 2019 with great differences across regions (World Bank, 2022). Not only ever more resources need to be spent on treating diseases attributable to air pollution exposure, but air quality degradation erodes individual and social well-being undermining the productive capacity of communities and countries in the long-run. In economic jargon, by damaging health, pollution reduces the rate of return of the most important asset, human capital, which is the basis of increased standard of living around the world. In Mexico, the majority of the population is overweight or obese (OECD, 2016) and thus vulnerable to diseases associated with air pollution, such as strokes or diabetes.

Intuitively, workers confronted with air pollution face a trade-off between protecting their health and maintaining their income (Hanna and Oliva, 2015). Additionally, some local governments have acknowledged the negative consequences of high air pollution in cities, and tried to address them with interventions either to reduce pollution (for example, by banning certain vehicles and by reducing the number of vehicles circulating), or to protect people by asking them to stay at home on high-pollution days. The latter approach thus presents a policy effect of air pollution on labour supply that is beyond an individual's control. Yet, all three factors - income, health and policy - containing important heterogeneities. An individual residing in a composite household will not only consider his or her own health, but also that of dependents within the household. Such a consideration might weigh more for women than men in societies where the care burden falls disproportionately on women (Aragón et al., 2017; Montt, 2018). On the income side, the constraint may be more binding for individuals whose job relies on their hourly productivity, for example, as it is the case for informal self-employed street vendors or piece meal workers. In contrast, a public sector employee with a monthly salary can safely stay at home on days of high-pollution (Hanna and Oliva, 2015; Hoffmann and Rud, 2022). The policy effect then interacts with the previous two.

In this study we ask how labour supply responses to air pollution vary across gender labour supply response, differentiating between policy, health, and income effects. First, we provide a theoretical of labour supply that illustrates the ambiguity of the health and income effects, proving that an increase in air quality should produce an increase in hours worked, unless a negative income effect dominates. It thus remains an empirical question to test whether this is the case. Then, we employ two empirical strategies applied to data from measurement stations and a representative labour force panel survey of Mexico City in the 2000's. We dispose of daily air pollution data and locations of ground measurement stations across the city, and consider a five-kilometre radius around them to match our survey data. The Mexican Employment and Occupation Survey (ENOE) is a quarterly survey with a rotating panel component that follows the same individuals over five quarters. It asks the workers about their daily hours worked in a reference and usual week, allowing us to link the daily labour supply to daily air pollution for the period from 2005 to 2010.

When pollution exceeds particular thresholds, Mexico City activates the "Environmental Contingency Program" tiers to a pre-contingency or a more severe contingency level. Pollution alerts (contingencies) are called when pollutants' concentration for Ozone or PM10 reach a given threshold in terms of an air quality index. Different alert levels entail cars being taken off the road and the closure of public sector work places, including schools. We exploit these thresholds and adopt a regression discontinuity design around the days before and after contingencies to document a reduction in the hours worked when a (pre)contingency is called. We then study how daily working hours evolve around a (pre)contingency and show how labour supply responds before and after its activation. Then, we apply a panel model to assess the daily labour supply responses by gender and formality status.

In order to capture the health effect, we consider the whole distribution of air pollution, by using a binned structure of thresholds from 0 to 70 as in Dell et al. (2014); Schlenker and Roberts (2009); Burke et al. (2015) that allows for a fully flexible association between pollution and labour supply. The income effect is identified by allowing for heterogeneity across formality status. The inclusion of fixed effects controls for time-invariant and time-varying unobservables, which could otherwise affect labour supply and air pollution simultaneously.

Differential effects by gender: there is an unequal gendered response to pollution exposure. For male workers the income effect dominates, and thus labour supply increases at high levels of pollution;

Female workers have a different trajectory:their minutes worked trajectory reduces as pollution rises, but informal female workers then display a big catch up at highest levels of pollution.

Recent contributions from economists have focused on the identification of mortality and health effects using administrative data, as well as have expanded the attention to school and labour market outcomes. In terms of identification, the introduction of policies (e.g., Chay and Greenstone (2003)) or natural experiments (e.g. Hanna and Oliva (2015); Borgschulte et al. (2022)) are generally explored, or alternatively events like wind direction or temperature inversions serve as instrumental variables (e.g., Deryugina et al. (2019)). Outcomes of interest cover from school absenteeism and test scores (e.g., Lavy et al. (2014)), to labour productivity of outdoor and indoor workers (e.g., Graff Zivin and Neidell (2012); Chang et al. (2016); He et al. (2019), hours worked (e.g. Aragón and Rud (2016); Hoffmann and Rud (2022); Aragón et al. (2017); Hanna and Oliva (2015)), absenteeism of workers and firms' sales (e.g. Leroutier and Ollivier (2022)), earnings (e.g. (Isen et al., 2017)), to cognition, e.g. exam performance (e.g. Stafford (2015); Ebenstein et al. (2016); Zhang et al. (2018)), and even long-lasting effects of hazardous pollutants on poverty trajectories (Persico, 2022).

Closely related to our work are the studies by Graff Zivin and Neidell (2012); Chang et al. (2016, 2019), who all find that high pollution reduces labour supply through the substitution effect. Aragón et al. (2017) show that in Lima, Peru, the labour supply effect varies along the pollution distribution and with household structure. Households with more dependents in need of care are more sensitive to moderate pollution levels and there is no intra-household re-allocation of labour so that earnings decline. In the specific of Mexico City, Hoffmann and Rud (2022) find a negative effect of high levels of air pollution on same-day labour supply. Further, they show that workers compensate by working more after such high-pollution days, however, with important heterogeneities. Informal workers reduce their labour supply by less and compensate less leading to an overall income loss. The authors conclude that avoidance behaviour and income constraints matter.

We are complementing and improving on the previous literature in two ways. First, we employ the most precise measure of air pollution for Mexico City, by applying a 5 kilometre radius and the census block to match the air pollution to labour force data. In this way, we account for the mountainous geography of Mexico City, which influences the local concentration of air pollution. Hoffmann and Rud (2022) use a radius of 20 kilometre and an interpolation method that relies on the centroid of local administrative units, which are relatively large. As comparison, there are 16 boroughs in Mexico City, each containing up to 133 census blocks. Second, we do not only consider one specific threshold of high air pollution. Rather, we allow for non-linear responses as in Aragón et al. (2017), and we account for heterogeneity by gender and employment type, as well as by before, during and after pre-contingencies' introduction. This approach allows us to disentangle the effect of pollution management policies from health and income effects on urban labour supply.

The article is organised as follows. In Section 2 we outline the Pollution policies in Mexico city. In Section 3 we briefly present the theoretical framework behind this research inquiry, and in Section 4 we present the quantitative data and descriptively assess how we define air pollution and for which population of urban workers. Section 5 provides the identification approach used for measuring the effect of pollution alerts on labour supply, as well as how ambient air pollution affects labour supply. Section 6 report an analysis of the policy effects to pollution events, the behavioural responses as well as an analysis of lagged responses. The article then concludes.

2 Pollution Policy in Mexico city

Mexico City has a persistent problem of air pollution, which poses significant health and environmental risks. To mitigate the impact of high levels of air pollution, the city has established a pollution contingency strategy. The strategy is a set of measures that are activated when air pollution levels exceed certain thresholds. The measures are aimed at reducing emissions and minimising exposure to pollutants.

One of the primary measures in the contingency strategy is the implementation of a traffic restriction program. When air pollution levels surpass certain limits, the program imposes restrictions on the circulation of vehicles based on their license plate number. The restrictions are enforced by a combination of traffic police and cameras throughout the city, with penalties for noncompliance. By reducing the number of vehicles on the road, this measure seeks to limit emissions and improve air quality.

Pollution has been a major concern for Mexico city since the 1980s, when the city introduced its flagship pollution management scheme in the form of the *Hoy No Circula* scheme. The scheme as runs in conjunction with a push to move major polluting industries outside the city. The scheme entails a permit system which governs the usage of private motor vehicles. Each day 1/5 of all cars older than 3 years must rest from driving for 1 day per week, and 1 Saturday a month. The evidence of the effectiveness of this policy is poor Davis (2008, 2017). This policy is coupled with a monitoring system on the amount of pollution in the city. Thirty three stations dotted across the city monitor pollution. The measurement of Ozone, and PM10 is then transformed into an air quality index called IMECA. If the IMECA index crosses a deterministic threshold (100 index points) then a pollution alert is called. At this stage the index would be publicised in the news and individuals asked to consider their outdoor air movements and reduce as appropriate.

Part of the pollution mitigation strategy for Mexico city includes public awareness campaigns that seek to inform residents of the risks associated with air pollution, and how to minimize their exposure to pollutants. These campaigns provide information on the health effects of air pollution, as well as advice on measures that individuals can take to protect their health during times of high air pollution. The city also maintains a real-time air quality monitoring system to keep residents informed about the current air quality conditions and the activation of contingency measures.

2.1 Pollution Alerts

The pollution contingency plan in Mexico City establishes a series of thresholds for air pollution levels that trigger a series of alerts and contingency measures. There are two primary pollutants that the city monitors: ozone and particulate matter, both of which have adverse health effects on the population. The thresholds for each pollutant are set based on World Health Organization (WHO) and Mexican environmental regulations. Table 1 provides the IMECA index cutpoints and their equivalent measures for Ozone and PM10.

Table 1: IMECA Air Quality index cutpoints valid in 2005–2010

IMECA AQI	Description to public	Ozone ppm	PM10 $\mu g/m^3$
0–50	Good	0.000-0.055	0–60
51–100	Normal	0.056–0.110	61–120
101–150	Bad	0.111–0.165	121–220
150–200	Very Bad	0.166–0.220	221–320
>200	Extremely Bad	>0.220	>320

Notes: The cutpoints in this table derive from the public policy in effect during our time period of analysis and derive from Mexico city environmental norm NADF-009-AIRE-2006. Note that the cutpoints are only reported for Ozone and PM10 the two pollutants over which pollution alerts may be called. Though there exist cut points for PM2.5 for the air quality index, but these are not relevant for the activation of public policy. So for example, should PM2.5 thresholds exceed the 150 threshold there would not be a pollution amber alert called. It is worth noting that the PM10 standard used for a precontingency exceeds the Interim target 1 measure of WHO outdoor air quality standards, which is the loosest air quality standard. The Standard for bad outdoor air quality in PM10 is 20, thus for some levels described to the public as good the actual pollution level is actually harmful to public.

For each pollutant, there are four different alert thresholds, each with a specific set of measures that are triggered. The first threshold, known as *precontingencia* (pre-contingency) is reached when the concentration of ozone exceeds 150 points on the ozone air quality index. During this stage, the authorities issue a warning and increase the frequency of air quality monitoring. They also ask the public to take voluntary actions such as reducing outdoor activities and avoiding physical exertion.

If the pollution concentration continues to rise, the contingency plan enters the a pollution yellow alert, known as *Fase 1* (Phase 1). Fase 1 is triggered when the ozone concentration reaches 150 points on the air quality index. During this stage, the authorities impose traffic restrictions, limiting the circulation of vehicles based on their license plate numbers. They also suspend some industrial activities and ask the public to take additional measures such as using public transportation or carpooling.

The pollution amber alert is Fase 2 (Phase 2) is triggered when the ozone concentration reaches 200 points on the air quality index. During this stage, more stringent measures are implemented, such as the closure of schools and certain industries. Additionally, the authorities may order the suspension of public transportation services, except for those that use clean energy sources.

A pollution red alert *Contingencia Ambiental Extraordinaria* (Extraordinary Environmental Contingency). This stage is triggered when the ozone concentration reaches 300 points on the air quality index. During this stage, the most stringent measures are implemented, such as the closure of all schools and the suspension of all industrial activities except those deemed essential. In addition, all public transportation services are suspended, and the circulation of vehicles is restricted to those considered essential.

Between 2005–2010 there were no yellow, amber, or red alerts. This is likely to the looseness of air quality standards. However, there were a number of pre-contingencies called during this period, it will be these periods of increased pollution salience which we will exploit for identification of the public policy effects.

3 Theoretical Framework

This section outlines the theoretical framework borrowed from Hanna and Oliva (2015). Partial Eq model where individuals maximise utility with respect to consumption c and hours worked e. Utility is given by $u = u(c, e; \alpha)$. Note that e is 'bad' in that that $u_e < 0$ and $u_c > 0$. Utility is assumed to be concave.

Air quality, α, is an argument of the utility function and affects consumption and hours worked.

Better air quality lowers disutility of work $u_{ea} > 0$ But effect can be ambiguous: better air quality may improve consumption ($u_{c\alpha} > 0$; think of amusement rides, or outdoor shopping). However, better air quality may also reduce marginal utility of consumption ($u_{c\alpha} < 0$; if say asthma medication or gym is substitute for clean air.)

3.1 Optimisation Problem

Using indirect utility approach one can write:

$$\max \nu(e) = \lambda(\alpha) \cdot we - g(e; \alpha)$$

Where w is wages in time t. Note that individuals are wage takers, and wages are assumed to be unaffected by pollution.

Marginal utility of lifetime income along optimal path is represented by $\lambda(\alpha)$

$g(e; \alpha)$ is disutility of hours for a given air quality

$$g(e; \alpha) = -\int_0^e u_e(x; \alpha) dx$$

The effect of pollution on hours worked is obtained via the solution to the FOC:

$$g_e(e; \alpha) = \lambda(\alpha) w$$

given the additive separability of hours and work, the change in hours worked as air quality increases this is:

$$\frac{de}{d\alpha} = \frac{\overbrace{-g_{e\alpha}}^{\text{substitution effect}} + \overbrace{\frac{\partial \lambda}{\partial \alpha} w}^{\text{income effect}}}{g_{ee}} \tag{1}$$

The first term is the "substitution effect". This has an expected positive sign due to the *decrease* in disutility of work decreasing in air quality). The second term is the "income effect". The overall sign of the income effect is ambiguous, we would expect it due to he term to be negative, thereby *decreasing* substitution effect, as better air quality may *decrease* utility gains from consumption if consumption is a substitute to air quality. However, if air quality is a complement to consumption, then marginal utility of income $\lambda(\alpha)$ could increase with better air quality.

4 Data and variables

4.1 Air pollution

This section outlines the pollution data used. As outlined earlier Pollution alerts (contingencies) are called when Ozone or PM10 reach a given threshold in terms of an air quality index. Crucially for the present analysis PM2.5 cannot trigger a pollution alert though it is highly likely that pollution alerts are correlated with higher that average levels of PM2.5. Over the time period investigated no alerts were called, but pre-contingencies were triggered.

Our data are drawn from the SIMAT network of pollution monitoring stations across the city operated by the Mexico city department of health. The data give hourly readings for each pollutant per station. We restrict our present analysis to 2005-2010 as for these years we can match the data at census block level with the Mexican Employment and Occupation Survey, a household labour market survey. For the period in question there are no alerts which led to any policy effects beyond increased salience via the appeal to increased awareness.

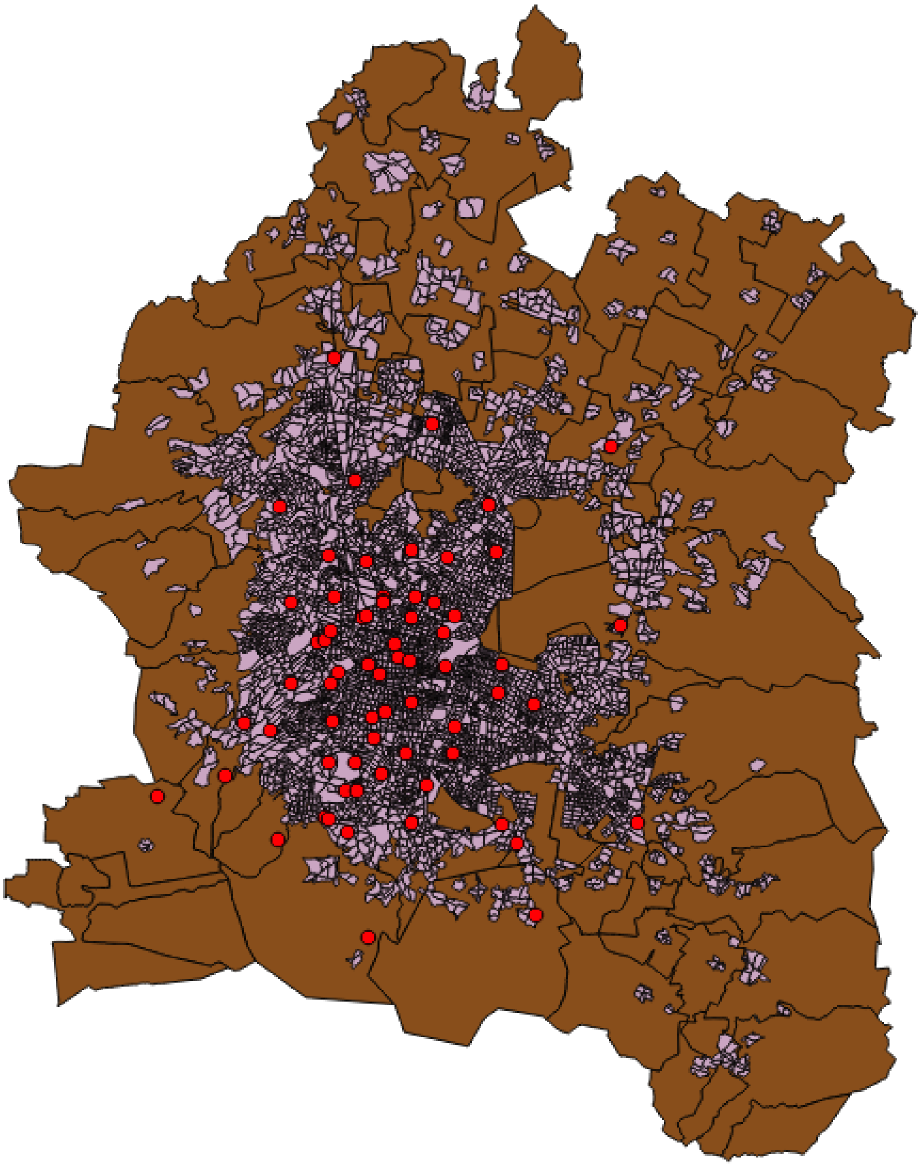
Figure 1 plots the distribution of the monitoring stations. The shapes in dark brown are the municipalities in the Greater Mexico city area, and the shapes in purple are the census blocks within Mexico city. Note that these data are markedly different to those used by Hoffmann and Rud (2022) who focus on daily *municipal* aggregate measurements of pollution. There are up to 133 census blocks per municipality, thus revealing significantly richer data, which we exploit to do a finer contrast with only 5km nearest observations compared to the 20km nearest employed by Hoffmann and Rud. We also differ from Hoffmann and Rud in terms of interest, in their paper they focus on the impact of extreme pollution events on labour supply, whereas we are interested in characterising the full impact across the whole distribution of pollution observed.

We take the station data and use inverse distance weighting to interpolate the pollution measure from point data to a raster similar to the approach adopted by Hanna and Oliva (2015). Specifically, we use the 5km nearest neighbours for the interpolation, and we follow the advice from de Mesnard (2013) and use a quadratic pollution radiation exponent. Thus the inverse distance weighting estimate for the $\overline{P}_j$ point is:

$$\overline{P}_j = \frac{\sum_{i=1}^{n_j} \frac{1}{d^2}}{\sum_{k-1}^{n_j} \frac{1}{d^2}}$$

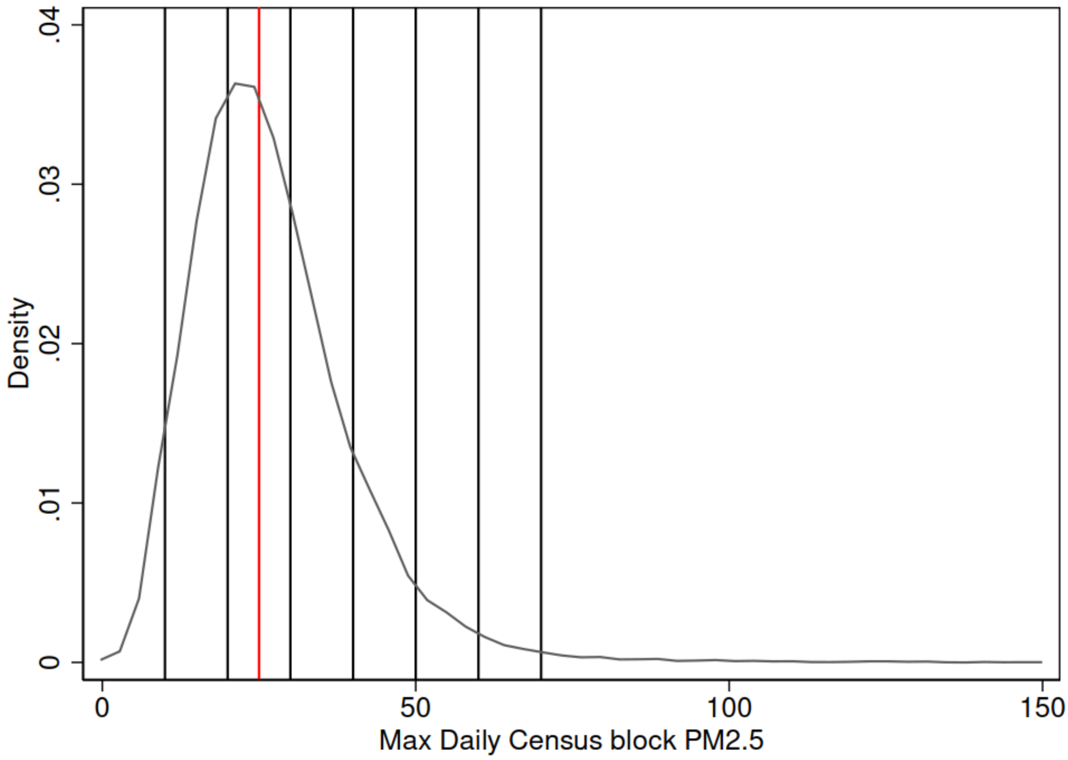
Where for a given j^{th} point, we compute the average pollution level P by taking the the 5km nearest neighbouring stations denoted n_j, and for each station we compute the d distance in km. Thus we can use the inverse distance denoted $1/d^2$ and weight the average of our observations by this. We compute a measure of the maximum level of pollution that a given census block experienced in a given day, as well as measures of cumulative hourly exposures.

Figure 1: Distribution of Pollution Stations in Mexico City



NOTE: Figure shows the Metropolitan Zone of Valley of Mexico (Greater Mexico City). Brown polygons represent municipal administrative borders. Purple polygons represent census blocks, or basic geostatistic units. Red point data refer to the 33 Pollution monitoring stations operated by SIMAT the Mexico City monitoring system.

Figure 2: Distribution of maxima PM2.5 hourly-census block



Note: Figure shows the distribution of Maximum Daily PM2.5 $\mu g/m^3$. The black lines denote the cutpoints for pollution bins. The line in red refers to the WHO Outdoor Air Pollution Interim Target 4 guideline, a measure that exceeds this threshold of PM2.5 can be considered to be of poor quality. It is evident that poor air quality is a common occurrence in our setting.

4.2 Labour supply measures

The daily pollution exposure data are matched by census block level to daily household labour force survey responses from the Mexican Employment and Occupation Survey (ENOE) for the period 2005q1–2010q2. This survey is a 5 quarter Rotating Panel for whom the data are representative at city level for Mexico City. Specifically we focus on whether those individuals who report as being employed are working in the given reference week. We can investigate the extensive margin (is working) against the extensive margin (the intensity of hours worked). We end up with 60,535 individuals across 18 quarters, which is 423,745 individual-days approximately distributed at about 3,000 observations per quarter. Figure 2 shows the distribution of maximum pollution levels observed across the hourly census blocks in the data.

4.3 Descriptive statistics

Table 2: Distribution of pollution in bins

bin	PM2.5 $\mu g/m^3$	Hours-census block (%)	Days-census block (%)
0	0–10	58.87	60.04
1	11–20	13.25	11.76
2	21–30	12.08	13.78
3	31–40	7.5	8.99
4	41–50	4.08	3.88
5	51–60	2.00	1.17
6	61–70	0.83	0.27
7	70+	0.67	0.12

Table 3: Individual characteristics by gender

	N	Total	Female	Male	t-test / χ^2
Female	60,535	0.420			
Age	60,535	39.152	38.934	39.309	-8.929
Informal (social protection)	60,535	0.574	0.565	0.581	-10.094
Informal in the informal sector	60,535	0.288	0.252	0.313	-43.555
Self-Employed	60,535	0.191	0.182	0.197	-11.881
Wage Worker	60,535	0.729	0.738	0.723	11.164
Worked Reference Week	60,535	0.450	0.456	0.445	7.512
Professional occupations	60,535	0.192	0.209	0.180	32,338.934
Managers, directors and senior officials	60,535	0.036	0.028	0.041	
Skilled trades occupations	60,535	0.252	0.120	0.348	
Administrative and secretarial occupations	60,535	0.152	0.196	0.120	
Sales and customer service occupations	60,535	0.208	0.235	0.188	
Caring, leisure and other service occupations	60,535	0.160	0.213	0.123	

Note: All t-test & χ^2 test are statistically different by gender.

Table 4: Individual characteristics by gender

	N	Total	Female	Male	χ^2
Manufacturing	60,535	0.144	0.128	0.157	36,243.955
Construction	60,535	0.054	0.009	0.086	
Trade	60,535	0.222	0.240	0.208	
Restaurants & Accommodation Services	60,535	0.064	0.079	0.053	
Transport, Communications, Post & Storage	60,535	0.083	0.031	0.120	
Professional, Financial & Corporate Services	60,535	0.125	0.120	0.129	
Social Services	60,535	0.113	0.175	0.068	
Diverse Services	60,535	0.119	0.148	0.098	
Government & International Organisations	60,535	0.077	0.071	0.081	

Note: All t-test & χ^2 test are statistically different by gender.

Table 5: Informality status by gender & employment

Employment Modality	Male	Female	All
Wage employment	.478	.468	.47
Self-Employment	.997	.998	.99
Private Sector	.657	.668	.66
Public Sector	.113	.104	.108

Note: All t-tests on proportions are statistically different by gender.

Table 6: Labor supply by work status: Daily minutes worked, by gender

Employment Modality	Male	Female	All
Wage employment	404.96	340.55	377.84
Self-Employment	396.40	282.99	350.91
Private Sector	407.00	331.96	377.12
Public Sector	373.31	320.79	348.10

Note: All t-test & χ^2 test are statistically different by gender.

Table 7: Person-days of pollution exposure in each bin, by gender

PM2.5 $\mu g/m^3$	Male	Female	Total
0-10	141,651	105,513	247,164
11-20	30,653	20,998	51,651
21-30	35,326	25,189	60,515
31-40	23,490	16,352	39,842
41-50	10,406	7,024	17,430
51-60	3,134	2,208	5,342
61-70	782	491	1,273
70+	314	214	528
Total	245,756	177,989	423,745

Note: All t-test & χ^2 test are statistically different by gender.

5 Identification method & Empirical approach

In this section we will outline the empirical approach we take in this paper. As outlined in the background section, Mexico has a pollution mitigation policy in place. The existence of this policy poses difficulties for the identification of the effect of pollution on labour supply. The pollution monitoring system SIMAT runs on a 24 hour basis but the salience to individuals is increased through a notification likely via news channels (print and TV) when an alert is raised. To mitigate this concern, we will seek to estimate two separate effects. The behavioural response to the increased salience of pollution, and the effect of pollution on labour supply. We exploit two features of the Mexican setting to allow this dual distinction. First, pollution policy depends exclusively on PM10 and Ozone readings. Our present analysis focuses exclusively on particulate matter smaller than 2.5 micrometres (PM2.5).

There is an imperfect correlation between days of high PM10 and PM2.5. It is not uncommon for high levels of PM2.5 to be experienced even at low levels of PM10. Thus, increased salience of pollution only occurs when other pollutants trigger pollution alerts, but not necessarily when there are high levels of PM2.5.

Thus the behavioural policy effects can be detected by exploiting a sharp regression discontinuity design exploiting the dates when a pollution pre-contingency was called, where as the potentially 'Physiological' Effects of pollution can be estimated by exploiting a high dimensional fixed effects strategy. We will now outline each strategy in turn.

5.1 Measuring the causal effect of pollution alerts on labour supply

Pollution alerts in Mexico city vary by the amount of pollution detected. Deterministically beyond some 'IMECA thresholds' there are citywide shutdowns. Notably not actually based on PM2.5. Furthermore, the public policy thresholds in effect over the time period under analysis all exceed what would be considered poor air quality. In this section we ask: 'What is the behavioural effect of the pollution abatement strategy on hours worked?'

To answer this question we rely on a sharp regression discontinuity design (RDD) exploiting the date of pollution notifications for the period 2005–2010.

$$Y_{cit} = \beta \text{Pollution Notification} + f(\text{daysto/from P event}) + X'\gamma + \omega_t + u_{cit} \tag{2}$$

Where Y_{cit} is the labour supply outcome of relevance either in the extensive margin, (i.e., an individual i in census block c is working in a given day t), or the extensive margin (i.e., conditional on working how many minutes did an individual i work on day t). ω is a vector of time fixed effects (viz.household, month, year-quarter, weekday, day of month) which mop up any seasonal, yearly or even household trends. $f(.)$ denotes a functional form for the running variable days to/from pollution increasing in salience. As with all RDDs the usual concerns apply regarding the existence of a discontinuity exists. The threat of manipulation is not credible. The average individual is unable to change the time that a pre-contingency is called. In terms of government intervention in the pre-contingency, it is unlikely as the SIMAT system is independently run and audited by the Centre for Atmospheric Studies of the UAM university and is routinely audited by scientists for calibration errors in the monitors.

Thus, the causal parameter of pollution alerts is given by β.

5.2 Measuring the effect of air pollution on labour supply

Pollution mitigation issues aside, the measurement of the effect of pollution on labour supply is problematic. There is an issue that there is no reason from the biomedical literature to believe there is a linear dose response function. A similar concern has been previously raised in the literature dealing with the effects of temperature on on labour market outcomes. We inform our preferred approach from that literature (Dell et al., 2014; Schlenker and Roberts, 2009; Burke et al., 2015).

Thus we propose to implement a binned structure for pollution variables to allow for a fully flexible association between pollution and outcome variables (Guerrero Compeán, 2013; Guiteras, 2009; Graff Zivin and Neidell, 2014; Barreca et al., 2016; Burgess et al., 2014; Schlenker and Roberts, 2009).

We therefore rely on a high-dimensional fixed effects strategy and estimate the following:

$$Y_{icdmwq} = \sum_{b=1}^{B=7} \Theta E_{cd} + \alpha_i + \delta_c + \gamma_q + \eta_d + \kappa_m + \epsilon_{icdmwq} \tag{3}$$

Where Y_{cidmwq} is the labour supply outcome of relevance either in the extensive margin, (i.e., an individual i in census block c is working in a given day d, in a given year-quarter q, in a given month m, in a particular day of the week w), or the extensive margin (i.e., conditional on working how many minutes did an individual i work in a given day d, in a given year-quarter q, in a given month m, in a particular day of the week w). E_{cd} is our discretised measure of pollution across seven bins. δ_c are Census block fixed effects, α_i Individual fixed effects. η_w give Day of the week fixed effect. γ_q is the Year-quarter fixed effect and finally κ_m are Month fixed effects.

It stands to reason that the high dimensional fixed effects will sweep-out any concerns related to temporal shocks such as seasonal effects, and so on. However, one major concern here is that the identifying assumptions on this type of strategy rely on the assumption that the effects are orthogonal to the covariates and capture all time-invariant heterogeneity across units. This can be $E(\epsilon_{icdmwq}|\alpha, \delta, \gamma, \eta, \kappa) = 0$. In addition to this there is also the usual stable unit treatment value assumption (SUTVA) wherein the treatment value, (i.e., the pollution effect) of a given individual is independent of the effect on others. However, this is very likely violated within households. A simple thought experiment will illustrate the issue. Consider an extended household comprised of a household head, their partner, a child and the mother of the household head. Imagine that the high levels of pollution have a stronger effect on the child in the household (World Health Organization, 2016; Bateson and Schwartz, 2007). This would then have a knock on effect on both the household head and the partner, assuming no additional support in care giving. Now, assuming strong gender norms, it is likely that this excess burden will then fall on the adult female in the household (be they head or partner). Thus, this shock will violate the SUTVA and have a heterogeneous effect for women. Now, for the Mexican labour market there is good evidence that grandmothers are some of the primary sources of childcare (Talamas Marcos, 2023). Under normal circumstances the existence of childcare would suggest that they would be able to pick up additional stresses due to a sick child. However, there is also ample evidence that the elderly are vulnerable to ambient air pollution (e.g. **?**). Thus, it is highly likely that idiosyncratic and covariate health shocks to children and elderly household members as predicted by the biomedical literature will likely make this assumption not hold. One way around this restriction would be to estimate separate effects for subgroups along the gender and household composition dimension.

6 Results

In this section we present the results of the present analysis. First we present estimates that speak to the behavioural effects of the pollution mitigation policy. Second, we discuss the results of the rich high-dimensional fixed effects strategy that seeks to characterise the effect of pollution on labour supply.

6.1 Pollution alerts decrease labour supply

In this section we present the first empirical result: Individual's labour supply is reduced as a result of pollution becoming more salient due to a pollution alert. We also uncover that there are substantially heterogeneous effects across gender and household composition. For all households, we also detect a strong catch up effect wherein individuals seek to compensate for the losses in labour due to behavioural changes.

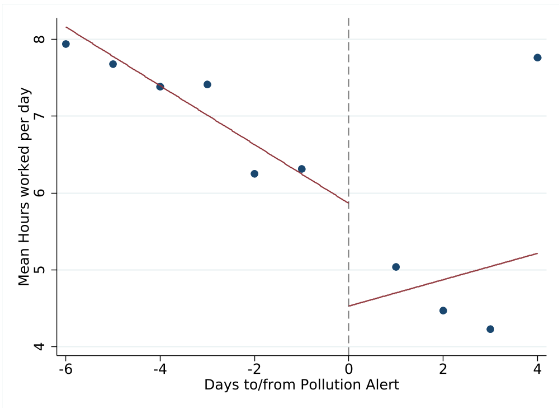
This evidence follows a number of stages. First, we will present the estimates from a graphical RDD approach, before presenting evidence from a local linear regression approach. Figure 5 provides the estimates for the intensive margin of productivity near the threshold of a pollution alert, or pre-contingency being called. From panel (a) it is clear that there is a decrease in the hours worked near the proximity of hours worked. The overall pattern that can be discerned suggests that average hours worked is decreasing ahead of the pollution alert. We interpret the decline in the averages as capturing a compound effect from physiological responses, that is individuals becoming ill and thus reducing their labour supply. It is notable that after a pollution event there is a marked period of catch-up in days 4+ where hours bounce back to their normal pre-pollution event mean. Panels (b) and (c) of Figure 5 disaggregate the estimates by sex and formality status. It is clear the slope is flatter for males, than females. As expected we observe a lower response from informal individuals likely reflecting the fact that informal individuals income is more exposed to actual working hours in a given day. This would be consistent with a negative income effect prevailing in our theoretic framework from equation 1.

For Female workers panel (c) shows a marked decrease in hours worked from the event of a pollution alert, with hours worked $\sim 75\%$ of normal the day after the event is called. This persists for a number of days, but by day 4, this reverts to the pre-pollution averages. Further to the concerns raised earlier about the impact on households by the composition of the household, we provide the first evidence that household composition matter matters for behavioural responses. Panel (d) provides some evidence for the effect of household composition on female worker's labour supply. As expected there is a divergence in behaviour on the basis of household composition that is markedly different from the overall population. Households with grandmothers and children (labelled 'childandabuela') see a steep reduction in labour supply in the days following a pollution alert with labour supply dropping to 2 hours per day. This suggests that grandmother's childcare role may be diminished during pollution alerts. This is some preliminary evidence that there may be covariate health shocks for children and grandmothers which impact on mother's ability to work.

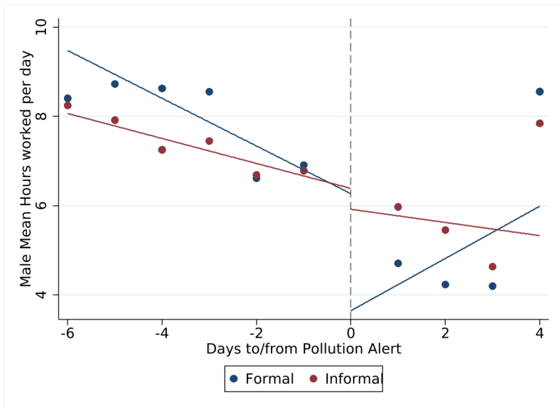
Table 8 provides the parametric estimates for a local linear regression with a 1 week window from the pollution alert. Columns 1–3 provide estimates for selected worker types whilst columns 4–6 replicate those estimates whilst taking out fixed effects for day of the

Figure 3: The Effect of Pollution alerts on labour supply intensive margin

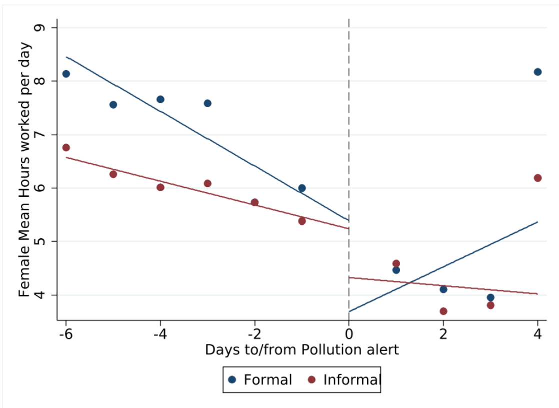
(a) All



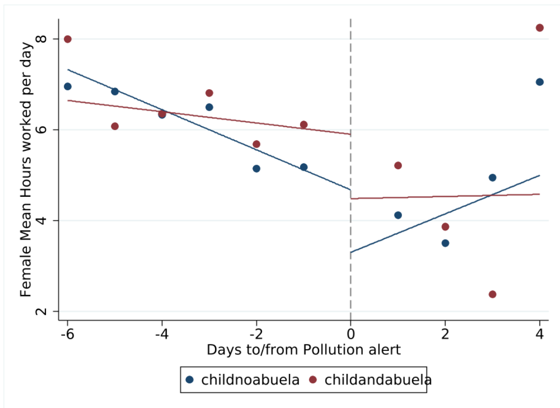
(b) Males



(c) Females



(d) Females by household composition



Note: Figures show the RDD estimates around the window of a pollution emergency. The lines are the linear bin scatters for the RDD either side of a pollution alert.

Table 8: The causal effect of pollution alerts on labour supply

	(1) All	(2) Informal	(3) Informal Women	(4) All	(5) Informal	(6) Informal Women
(a) All Households						
Pollution Alert	-65.087***	-49.376	-1.058	147.457***	147.539***	214.953***
	(25.085)	(33.879)	(44.064)	(36.497)	(48.497)	(71.919)
R^2	0.26	0.18	0.20	0.39	0.28	0.31
N	9,794	5,611	2,450	9,794	5,611	2,450
FEs	No	No	No	Yes	Yes	Yes
(b) Households with Children and Grandmothers						
Pollution Alert	-66.331**	-55.260	-48.557	121.824***	125.399**	125.679
	(30.824)	(41.863)	(54.705)	(44.941)	(58.201)	(88.331)
R^2	0.26	0.18	0.23	0.38	0.27	0.33
N	6,267	3,634	1,543	6,267	3,634	1,543
FEs	No	No	No	Yes	Yes	Yes
(c) Households with Children only						
Pollution Alert	-62.170	-24.915	143.425*	196.144***	187.312**	373.158***
	(43.589)	(60.662)	(74.093)	(61.388)	(85.392)	(111.974)
R^2	0.27	0.19	0.17	0.42	0.32	0.32
N	3,527	1,977	907	3,527	1,977	907
FEs	No	No	No	Yes	Yes	Yes

Note: Each cell reports the β parameter from equation (2). Each cell represents the estimates for a local linear parametric RDD employing a 6 day window of effects using a linear functional form. Columns 1–3 report no fixed effects, whereas columns 4–6 report the estimates that introduce time and household fixed effects. The standard errors are all clustered at the household level to account for within household correlations.

month, weekday, quarter year fixed effects and household fixed effects. The estimates all refer to the number of minutes worked. It is notable that the evidence from columns 1–3 suggests weakly that there is approximately a 60 minute reduction in hours worked. However, when conditioning on fixed effects the signs flip. This suggests that the catch up effect may dominate the initial drop in minutes worked.

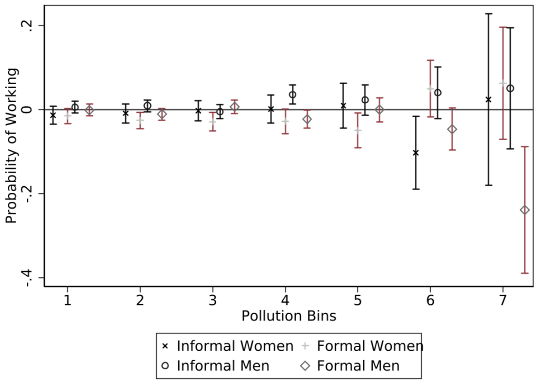
6.2 Does ambient air pollution affect labour supply?

In this section we discuss the second empirical finding of this paper: Labour supply is differentially affected by formality status, gender and household composition. Note that the estimates presented here exclude all weeks that contain a pollution alert to avoid the estimates being tainted by the public policy effect.

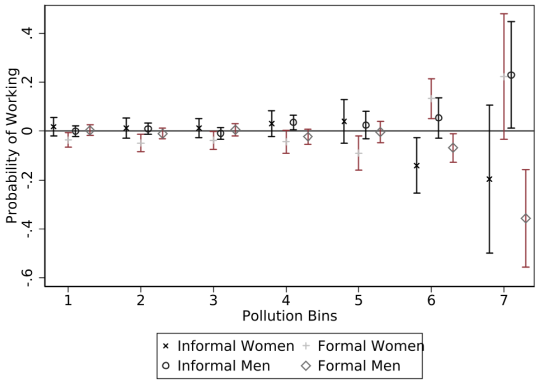
Figure 4 report the estimates from equation 3. The estimates are the results of a high dimensional fixed effects strategy that tackles the potential non-linearity in pollution effects by discretising pollution into seven bins of daily PM2.5 exposure. The panels show the estimates across different household types. The effects of pollution across all households are found to largely not affect the extensive effect of pollution, with some notable exceptions in

Figure 4: The Effect of Pollution on labour supply extensive margin, by gender and formality status and household composition

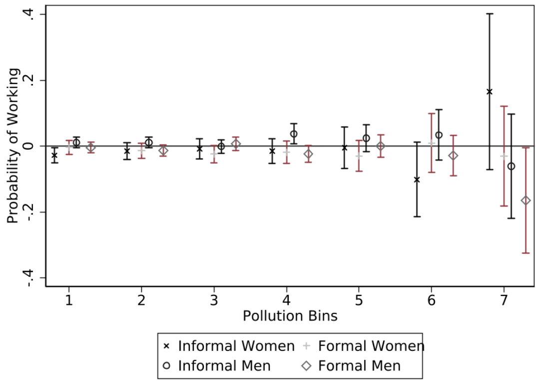
(a) All Households



(b) Households with Children



(c) Households with Children and Grandmothers

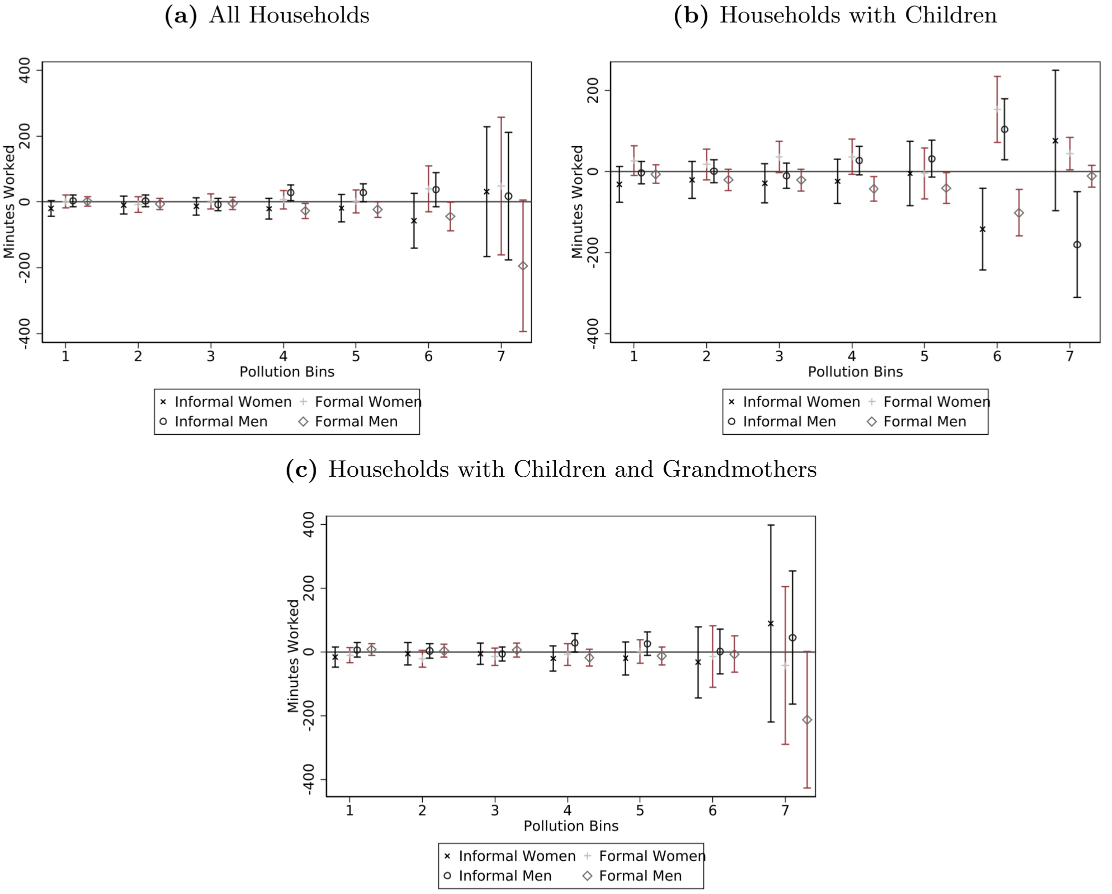


NOTE: Figure shows . There is a markedly lower shift of informal employment of men particularly between bin 2 to 4 (and 3 to 4).

the extreme pollution days.

Figure 5 replicates the analysis using the intensive margin of hours worked, that is in terms of minutes worked. Conditional on working the results suggests there is little effect of pollution on labour supply on aggregate. However, when household composition is taken into account a stark story develops. The overall aggregate effect on hours worked seems to be driven by childcare availability in the household, as there are significantly different labour supplies for workers who have children in the household particularly at acute pollution exposures (those greater than PM 2.5 of $60\mu g/m^3$). When compared to extended households who have grandmothers, this drop in labour supply seems to be mitigated, giving further evidence of the importance of grandmothers in providing childcare.

Figure 5: The Effect of Pollution on labour supply intensive margin, by gender and formality status and household composition



NOTE: Figure shows

7 Discussion

References

Aragón, F. M., J. J. Miranda, and P. Oliva (2017). Particulate matter and labor supply: The role of caregiving and non-linearities. *Journal of Environmental Economics and Management 86*, 295–309. Special issue on environmental economics in developing countries.

Aragón, F. M. and J. P. Rud (2016). Polluting industries and agricultural productivity: Evidence from mining in ghana. *The Economic Journal 126*(597), 1980–2011.

Barreca, A., K. Clay, O. Deschenes, M. Greenstone, and J. S. Shapiro (2016). Adapting to climate change: The remarkable decline in the us temperature-mortality relationship over the twentieth century. *Journal of Political Economy 124*(1), 105–159.

Bateson, T. F. and J. Schwartz (2007). Children's response to air pollutants. *Journal of Toxicology and Environmental Health, Part A 71*(3), 238–243.

Borgschulte, M., D. Molitor, and E. Y. Zou (2022, 09). Air Pollution and the Labor Market: Evidence from Wildfire Smoke. *The Review of Economics and Statistics*, 1–46.

Burgess, R., O. Deschenes, D. Donaldson, and M. Greenstone (2014). The unequal effects of weather and climate change: Evidence from mortality in india.

Burke, M., S. M. Hsiang, and E. Miguel (2015). Global non-linear effect of temperature on economic production. *Nature* (1), 1–16.

Chang, T., J. Graff Zivin, T. Gross, and M. Neidell (2016, August). Particulate pollution and the productivity of pear packers. *American Economic Journal: Economic Policy 8*(3), 141–69.

Chang, T. Y., J. Graff Zivin, T. Gross, and M. Neidell (2019, January). The effect of pollution on worker productivity: Evidence from call center workers in china. *American Economic Journal: Applied Economics 11*(1), 151–72.

Chay, K. Y. and M. Greenstone (2003). The impact of air pollution on infant mortality: Evidence from geographic variation in pollution shocks induced by a recession. *The Quarterly Journal of Economics 118*(3), 1121–1167.

Davis, L. W. (2008, February). The Effect of Driving Restrictions on Air Quality in Mexico City. *Journal of Political Economy 116*(1), 38–81.

Davis, L. W. (2017). Saturday Driving Restrictions Fail to Improve Air Quality in Mexico City. *Scientific Reports 7*(41652).

de Mesnard, L. (2013). Pollution models and inverse distance weighting: Some critical remarks. *Computers & Geosciences 52*, 459–469.

Dell, M., B. F. Jones, and B. A. Olken (2014). What do we learn from the weather? the new climate–economy literature. *Journal of Economic Literature 52*(3), 740–798.

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

Ebenstein, A., V. Lavy, and S. Roth (2016, October). The long-run economic consequences of high-stakes examinations: Evidence from transitory variation in pollution. *American Economic Journal: Applied Economics 8*(4), 36–65.

Graff Zivin, J. and M. Neidell (2012, December). The impact of pollution on worker productivity. *American Economic Review 102*(7), 3652–73.

Graff Zivin, J. and M. Neidell (2014). Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics 32*(1), 1 – 26.

Guerrero Compeán, R. (2013). Weather and welfare: Health and agricultural impacts of climate extremes, evidence from mexico.

Guiteras, R. (2009). The impact of climate change on indian agriculture. *Manuscript, Department of Economics, University of Maryland*.

Hanna, R. and P. Oliva (2015). The effect of pollution on labor supply: Evidence from a natural experiment in Mexico City. *Journal of Public Economics 122*(C), 68–79.

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

Hoffmann, B. and J. P. Rud (2022, January). Exposure or income? the unequal effects of pollution on daily labor supply. Working Papers 109, Red Nacional de Investigadores en Economía (RedNIE).

Isen, A., M. Rossin-Slater, and W. R. Walker (2017). Every breath you take—every dollar you'll make: The long-term consequences of the clean air act of 1970. *Journal of Political Economy 125*(3), 848–902.

Lavy, V., A. Ebenstein, and S. Roth (2014, October). The Impact of Short Term Exposure to Ambient Air Pollution on Cognitive Performance and Human Capital Formation. NBER Working Papers 20648, National Bureau of Economic Research, Inc.

Leroutier, M. and H. Ollivier (2022). The cost of air pollution for workers and firms. Job market paper, Stockholm School of Economics.

Montt, G. (2018). Too polluted to work? the gendered correlates of air pollution on hours worked. *IZA Journal of Labor Economics 7*(1), 7.

OECD (2016). Oecd reviews of health systems: Mexico 2016. Technical report, OECD Publishing, Paris.

Persico, C. (2022, October). Can pollution cause poverty? the effects of pollution on educational, health and economic outcomes. Working Paper 30559, National Bureau of Economic Research.

Roy, R. and N. A. Braathen (2017). The rising cost of ambient air pollution thus far in the 21st century. (124).

Schlenker, W. and M. J. Roberts (2009). Nonlinear temperature effects indicate severe damages to us crop yields under climate change. *Proceedings of the National Academy of sciences 106*(37), 15594–15598.

Stafford, T. M. (2015). Indoor air quality and academic performance. *Journal of Environmental Economics and Management 70*, 34–50.

Talamas Marcos, M. A. (2023). Grandmothers and the gender gap in the mexican labor market. *Journal of Development Economics 162*, 103013.

Vos, T., S. S. Lim, C. Abbafati, K. M. Abbas, M. Abbasi, M. Abbasifard, M. Abbasi-Kangevari, H. Abbastabar, F. Abd-Allah, A. Abdelalim, M. Abdollahi, I. Abdollahpour, H. Abolhassani, and 1017 other authors (2020, oct). Global burden of 369 diseases and injuries in 204 countries and territories, 1990–2013: a systematic analysis for the Global Burden of Disease Study 2019. *The Lancet 396*(10258), 1204–1222.

World Bank (2022). The global health cost of pm2.5 air pollution : A case for action beyond 2021. Technical report, World Bank, Washington, D.C.

World Health Organization (2016). Ambient air pollution: A global assessment of exposure and burden of disease.

Zhang, X., X. Chen, and X. Zhang (2018). The impact of exposure to air pollution on cognitive performance. *Proceedings of the National Academy of Sciences 115*(37), 9193–9197.