When the Boundary Layer Drops

Air Quality and Healthcare Use in Mexico

Piero Basaglia[1,2] Luis Sarmiento[3,4,5]

[1]Bordeaux School of Economics, CNRS, INRAE
[2]CESifo, Munich
[3]ETH Zurich [4]Banco de México
[5]EIEE

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All eyes on Davos...

Short term (2 years)	Long term (10 years)
1. Geoeconomic confrontation	1. Extreme weather events
2. Misinformation and disinformation	2. Biodiversity loss and ecosystem collapse
3. Societal polarization	3. Critical change to Earth systems
4.	4.
5.	5.
6.	6.
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9.	9.
10.	10.

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9.	Pollution	9.	
10.		10.	Pollution

Motivation

- Air pollution has been shown to have causal negative effects on economic outcomes via health effects
- Need for empirical evidence so far to understand which environmental policies would be socially desirable, but...
  - ⇒ almost only from developed countries (Barwick et al., 2024b, *REStud*)
  - ⇒ mortality focus - concentrates among elderly (Deryugina et al., 2019, *AER*)
  - ⇒ traditionally focus on selected clinical conditions (He et al., 2019, *JEEA*)
- **Currently.** Dose-response functions from US/Europe to inform policymaking in developing countries (Arceo et al., 2016, *Econ. J.*)

⇒ **This paper.** First economy-wide causal estimates of air pollution impacts on hospital visits in a non-high-income setting

Concerns with benefit-transfer methods: Examples

$PM_{2.5}$ pollution concentration ($1\ \mu g/m^3 \uparrow$)

$\neq$ Defensive behaviour

e.g. housing stock quality

$\neq$ Baseline pollution levels

e.g. non-linear effects

$\neq$ Health outcomes

This paper

- **Questions**
  1. What is the impact of $PM_{2.5}$ on overall nationwide hospitalizations?
  2. How are the effects distributed across demographic groups?
  3. Which are the underlying health conditions driving the effect?
  4. Do we observe nonlinearities across baseline pollution?
- **Outcomes**
  - Emergency room admissions in public hospitals by ICD-10 diagnosis from the Ministry of Health in México
- **Identification**
  - Quasi-random shocks in $PM_{2.5}$ exposure due to dynamic variations in the height of the planetary boundary layer (PBL) across municipalities
- **Key findings**:
  1. 1 $\mu g/m^3$ $PM_{2.5}$ shock $\Rightarrow$ 2.3% rise in hospitalizations for <u>all</u> conditions
  2. The most affected demographic group is children on average
  3. Due to respiratory conditions.. but also still unexplored health issues
  4. Effects increase non-linearly with exposure levels... but diminishing rate

Outline

1. **Empirical setting**
2. **Identification strategy**
3. **Average causal effects**
4. **Heterogeneity analyses**
5. **Remarks**

Contributions

- **Health costs of pollution**
  - Health: Deschenes et al. (2017); Deryugina et al. (2019); Anderson (2020); Barreca et al. (2021); Margaryan (2021); Graff Zivin et al. (2023); Klauber et al. (2024); Barwick et al. (2024b)
  - **Limitations**. (a) specific/narrow demographics (b) mortality effects only; (c) policy shocks: low-emission zones; (d) high-income settings
- **Private adaptations to environmental shocks**
  - Defensive expenditures: Deschenes et al. (2017); Sun et al. (2017); Zhang and Mu (2018); Ito and Zhang (2020)
  - Avoidance behaviours: Moretti and Neidell (2011); Zivin et al. (2011); Chen et al. (2020)
  - Role of information: Neidell (2009); Zivin and Neidell (2009); Janke (2014); Mastromonaco (2015); Barwick et al. (2024a)
  - **Limitations**. Heterogeneity (Drupp et al., 2025 for a recent review)

Empirical setting: México

Relevance

- Universal healthcare, *Seguro Popular* $\Rightarrow$ representative analysis by demographics (cf. Cohen and Dechezleprêtre, 2022)
- $\approx$ 70.9% of the population ($\approx$ 85M) has public healthcare (INEGI, 2020)
- Nationwide digital records of health services in all public hospitals
- Large heterogeneity in $PM_{2.5}$ pollution to leverage ($\Rightarrow$ 1.5 $\mu g/m^3$ - 122 $\mu g/m^3$)

Main data sources

Map of municipalities

Hospitalizations by ICD-10 code
Ministry of Health

Frequency: Daily

Detailed information at the admission level on **hospital visits** from the health information system of the Mexican Health Ministry (from 2008 onward)

Satellite-based PM2.5 estimates
Van Donkelaar et al.

Frequency: Monthly

0.01 X 0.01° gridded values of monthly PM2.5 estimates combining aerosol optical depth (AOD) data from NASA with a chemical transport model

Weather data
ECMWF

Frequency: Hourly

Re-analysis estimates of **weather variables**, such as air **temperature**, **precipitation**, and **atmospheric pressure** from the ERA5 data product

Planetary boundary layer height
ECMWF

Frequency: Hourly

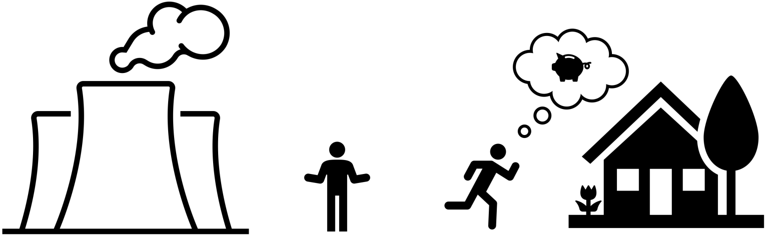
Re-analysis estimates of hourly variation in the **planetary boundary layer height** from the ERA5 data product

Spatial matching process → **Municipality-by-month estimation dataset (2008 -2022)**

Descriptive statistics (selected)

	Average	Standard Deviation	Maximum	Minimum	Units
Admission Rates					
General	157.31	188.26	4273.71	0.00	per 10,000 people
Male	117.74	151.43	3332.14	0.00	per 10,000 people
Female	194.78	228.96	5172.77	0.00	per 10,000 people
Age 0-12	166.03	232.06	4367.28	0.00	per 10,000 people
Age 12-20	152.22	181.13	4395.47	0.00	per 10,000 people
Age 20-40	183.55	215.80	5208.89	0.00	per 10,000 people
Age 40-60	116.33	160.36	3044.87	0.00	per 10,000 people
Age 60-80	148.93	216.60	3746.16	0.00	per 10,000 people
Age 80-130	224.57	332.84	6698.20	0.00	per 10,000 people
Population	148841.70	255942.80	1985601.91	1037.00	per 10,000 people
Main conditions					
Respiratory/Cardiovascular	34.45	49.12	1035.16	0.00	per 10,000 people
External Causes	25.46	31.23	871.54	0.00	per 10,000 people
Obstetric	14.03	24.20	596.09	0.00	per 10,000 people
Digestive	12.55	15.41	327.27	0.00	per 10,000 people
Infectious	12.50	20.55	810.19	0.00	per 10,000 people
Abnormal Clinical Findings	11.79	18.75	730.69	0.00	per 10,000 people
Eye/Ear	2.83	4.88	129.26	0.00	per 10,000 people
Rest of Conditions	49.73	65.32	1336.04	0.00	per 10,000 people
Weather					
Temperature	19.95	5.01	37.03	3.56	C
Dew Temperature	12.35	7.09	25.62	-12.07	C
Rain	35.71	42.48	639.36	0	m^3/m^2
Air Pollution					
PM2.5	16.46	7.58	121.64	1.52	μgm^3
PM2.5 Weighted	17.29	7.52	102.83	2.02	μgm^3

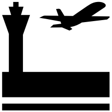
Endogeneity: e.g., Residential sorting



See for example Chay and Greenstone (2005); Lee and Lin (2018); Heblich et al. (2021).

Addressing endogeneity: Previous literature

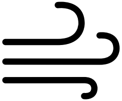
⇒ Two remarks: (i) low-frequency instruments; and (ii) first stage interpretability



Airport congestion
Schlenker and Walker (2016)

Volcanic eruptions
Halliday et al. (2019)

Public transport strikes
Knittel et al. (2016)



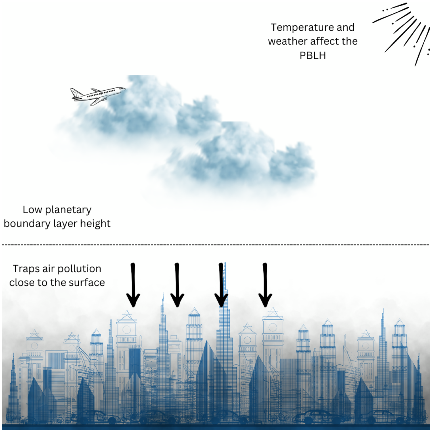
Wind patterns
Deryugina et al. (2019)

Boat traffic variation
Moretti and Neidell (2011)

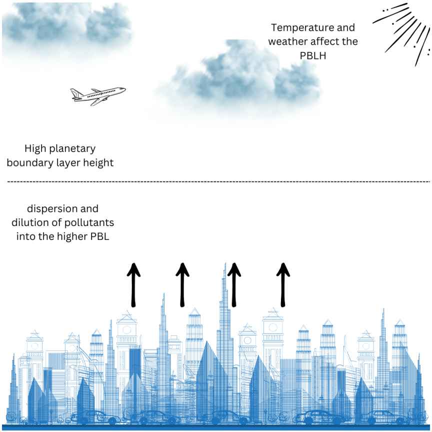
Economic recessions
Chay & Greenstone (2003)

Estimation strategy: IV approach

Planetary boundary layer height and air pollution



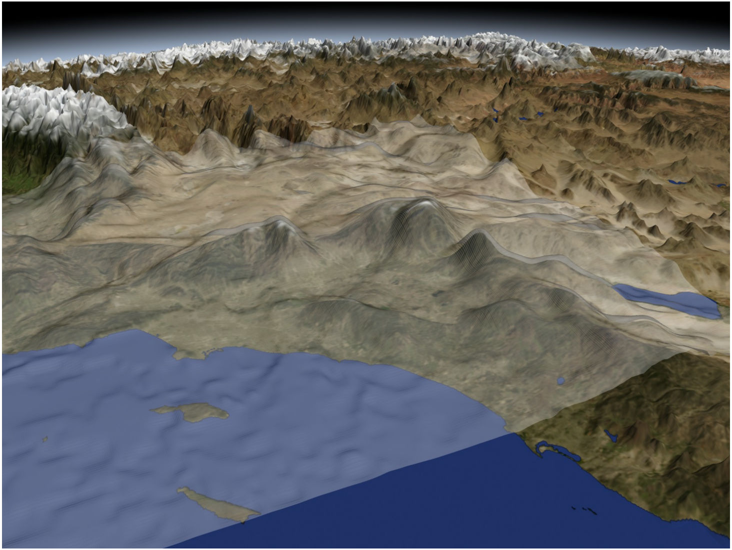
a) Low PBLH conditions



b) High PBLH conditions

See Schwartz et al. (2017); Godzinski and Castillo (2021); Kögel (2022); Dechezleprêtre and Aranciba (2024).

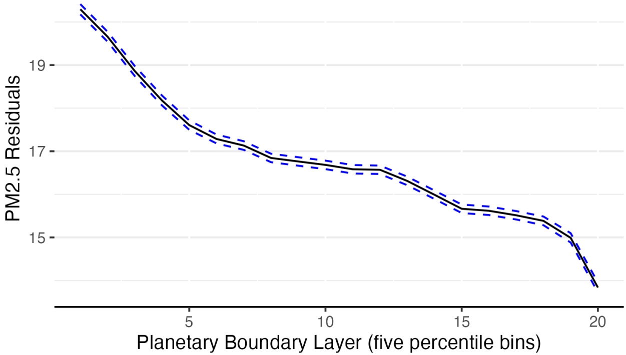
Dynamic variation in the PBLH



Credits to NASA's Goddard Space Flight Center Scientific Visualization Studio

Instrumental variable

- **Definition.** Arithmetic mean[1] of the PBLH of all hours within each day for each municipality ⇛ variation in monthly-weighted-average-by-municipality
- **Relevance.** We divide PBLH into five-percentile intervals and estimate the average PM2.5 while accounting for fixed effects for each municipality
  - ⇒ The difference between the lowest and highest five-percentile intervals is 32%



[1] We also estimate the maximum, minimum, and standard deviation of the PBLH for robustness exercises.

Identification strategy Reverse causality?

$\Rightarrow$ High-dimensional Fixed-effects Poisson Pseudo-Maximum Likelihood Estimator
$+$ bootstrapped nonparametric standard errors to account for using fitted values in the econometric design (Lin and Wooldridge, 2019)

$$PM2.5_{ct} = \omega_{ct} \times \left[\beta PBLH_{ct} + \gamma X'_{ct} + \delta_{ct} + \phi_{cy} + \epsilon_{ct} \right] \tag{1}$$

$$ER_{ct} = \omega_{ct} \times \left[\exp\left(\beta PM\hat{2}.5_{ct} + \gamma X'_{ct} + \delta_{ct} + \phi_{cy} \right) + \epsilon_{ct} \right] \tag{2}$$

- $PM\hat{2}.5_{ct}$: average value of $PM_{2.5}$ for municipality c at time t
- ER_{ct}: number of emergency room visits for municipality c at time t
- X'_{jt}: vector of controls
- δ_{cm}: municipality-by-month-of-the-year fixed effects
- ϕ_{cy}: municipality x year, y, fixed effects
- ϵ_{ct}: idiosyncratic error term
- ω_{ct}: weights reflecting the population in each municipality c at time t

Average causal effects on hospitalization visits

Morbidity interpretation

	Naive	Less naive	**Baseline**
	0.004***	0.008***	0.023***
	(0.002)	(0.002)	(0.006)
Fitted Statistics			
R2	1.019	1.016	1.006
# Obs	84034	84034	83666
# Municipalities	648	648	648
# Periods	155	155	155
F.Stat (first stage)	71.744	101.124	100.328
Mean admission rate per 10k	167.59	167.59	167.59
Average municipal population	148.793	148.793	148.793
Fixed Effects			
Municipality	✓	✓	✓
Year		✓	✓
Month		✓	✓
Municipality-by-month			✓
Municipality x Year			✓
Controls			
Weather		✓	✓

Putting magnitudes into perspective

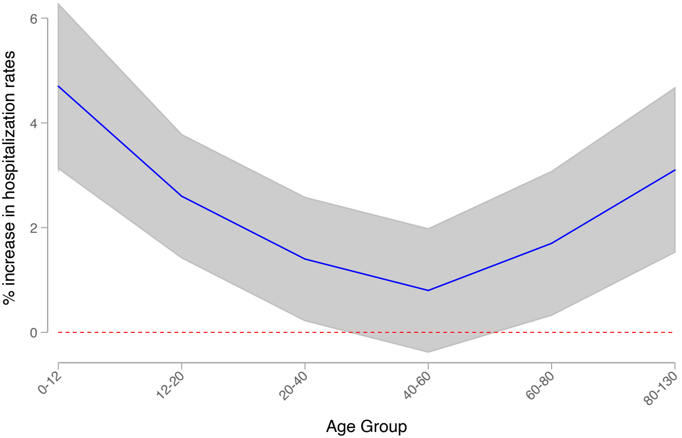
- Simple linear interpolation based on our estimates to assess the costs of $PM_{2.5}$ concentrations (17 mg/m^3) relative to WHO's recommended level of 10 ug/m^3
- From the Mexican Health Ministry: material and human costs associated with each admission $\rightarrow$ 4,200 MXP

Table 1: Direct morbidity costs associated with exceeding WHO standards for $PM_{2.5}$

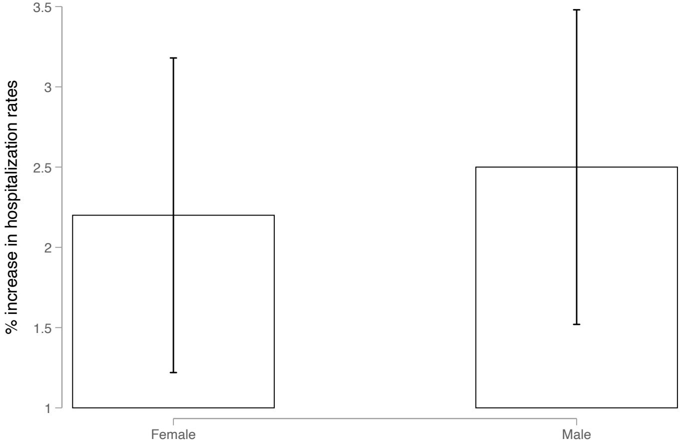
United States (Deryugina et al., 2019)	**Our study: Mexico**	**China** (Barwick et al., 2024)
0.25%	0.5%	1.5%

$\Rightarrow$ Previous evaluations using the benefit-transfer approach may underestimate the morbidity costs of air pollution by as much as $\sim$ 2 - 6 times in non-OECD countries.

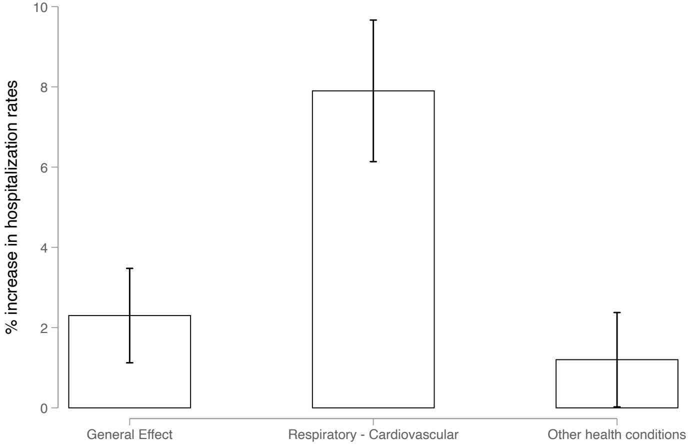
Heterogeneity by demographics



Heterogeneity by gender



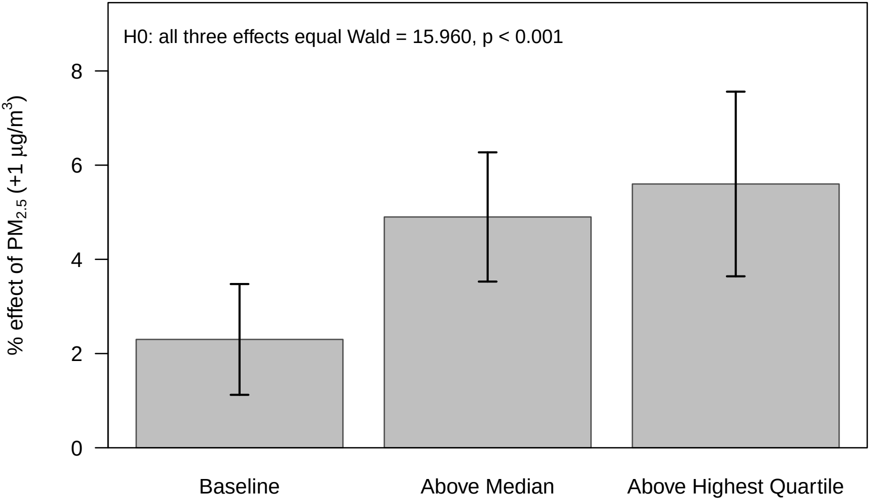
Heterogeneity by diagnosis I



Heterogeneity by diagnosis II

ICD-10 Code	Estimate	F-Value	#Obs	PR2	Cor2	MRate	Pop	PM2.5
Respiratory	0.0911*** (0.0107)	100.33	82507	1.02	0.88	30.7	148793.06	17.29
Eye and ear	0.0286*** (0.0079)	110.71	77647	1.14	0.87	3.1	148793.06	17.29
Abnormal clinical findings	0.0228** (0.0107)	110.71	78949	1.03	0.87	12.4	148793.06	17.29
Infectious	0.0175* (0.0093)	110.71	79217	1.03	0.89	13.7	148793.06	17.29
Perinatal	0.0151 (0.0190)	100.33	72519	6.02	0.83	0.45	148793.06	17.29
Other	0.0141* (0.0084)	110.71	79052	1.01	0.95	23.5	148793.06	17.29
Endocrine	0.0137 (0.0108)	110.71	79080	1.06	0.88	5.2	148793.06	17.29
Obstetric	0.0131 (0.0105)	100.33	81692	1.02	0.93	14.4	148793.06	17.29
Nervous	0.0120 (0.0098)	100.33	81483	1.22	0.83	1.9	148793.06	17.29
External causes	0.0114* (0.0066)	110.71	79802	1.01	0.94	26.5	148793.06	17.29
Neoplasms	0.0104 (0.0146)	100.33	77861	1.55	0.85	0.85	148793.06	17.29
Skin	0.0083 (0.0091)	100.33	81154	1.13	0.88	3.2	148793.06	17.29
Digestive	0.0048 (0.0069)	110.71	79437	1.02	0.92	13.4	148793.06	17.29
Muskuloskeletal	0.0032 (0.0072)	110.71	78507	1.07	0.91	5.03	148793.06	17.29
Genitourinary	0.0031 (0.0065)	110.71	79351	1.03	0.93	10.6	148793.06	17.29
Circulatory	0.0001 (0.0085)	110.71	79218	1.06	0.89	5.8	148793.06	17.29
Mental and behavioral	-0.0159 (0.0101)	110.71	78813	1.12	0.84	2.3	148793.06	17.29

Nonlinearities: Heterogeneous effects by baseline $PM_{2.5}$



Discussion

- First economy-wide causal estimates of air pollution impacts on hospital visits in a non-high-income context
- Focusing on mortality only might underestimate the health impacts on other demographics (e.g., especially pediatric and younger patients)
- Air pollution exposure might exacerbate infectious diseases and other health conditions beyond those traditionally investigated
- Previous evaluations based on benefit-transfer may largely underestimate pollution-driven morbidity costs

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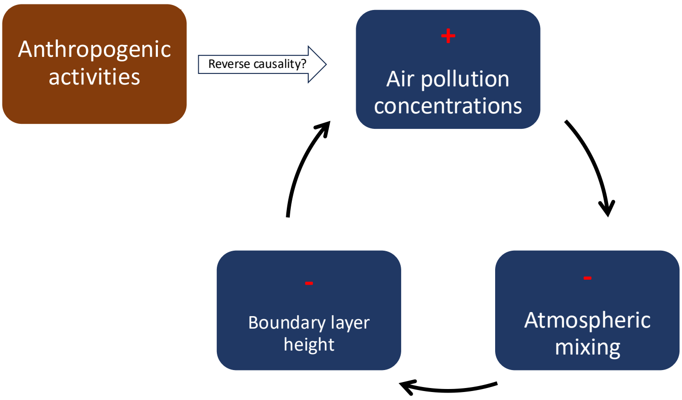
Appendix

Municipalities Back

Reverse causality Back

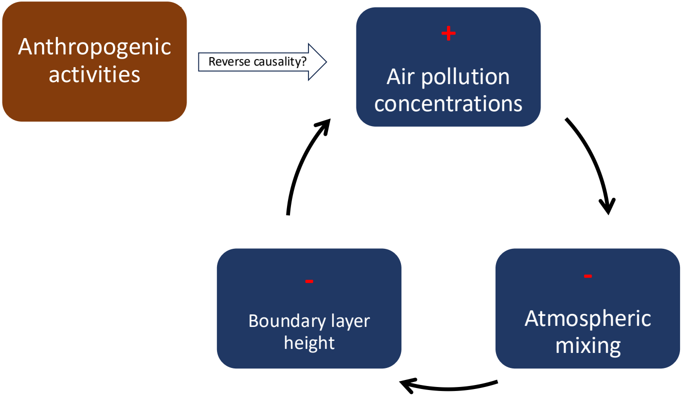
- **Concern?** Higher pollution levels can influence atmospheric mixing by altering radiative forcing (Bond et al., 2013), which could then, in theory, affect the PBLH.



Reverse causality Back

- **Modeling evidence from Petäjä et al. (2016):** Assuming baseline PM of 100, 200 or 250 μg m^{-3}, the corresponding strength of the feedback (i..e, % PBLH reduction) is about 1, 2 and 5% for ΔPM < 10 μg m^{-3}, about 3, 5 and 12% for ΔPM of 20 μg m^{-3}, and 6, 13 and >50% for ΔPM of 40 μg m^{-3}.

$\Rightarrow$ Within our setting, reverse causality can therefore plausibly be ruled out.



Average causal effects on hospitalization visits by type Back

	Home	Hospitalization	Death	Unspecified
Second stage β from Eq. 2				
$PM_{2.5}$ ($\mu g/m^3$)	0.03008***	0.01561	-0.02597	-0.10523
	(0.00543)	(0.00962)	(0.01910)	(0.06714)
Model Statistics				
Observations	83506	83076	62637	76994
Municipalities	648	648	648	648
F-Value (first stage)	100.33	100.33	100.33	100.33
Admission Rate (per 10k)	1419.75	211.20	1.71	43.25
Avg. Population	148,793	148,793	148,793	148,793
Fixed Effects				
Municipality × month-of-the-year	✓	✓	✓	✓
Municipality × year	✓	✓	✓	✓
Controls				
Weather variables	✓	✓	✓	✓

Nonlinearities: Heterogeneous effects by baseline $PM_{2.5}$

Table 2: Heterogeneous effects by $PM_{2.5}$ average exposure levels

	Median Split		Quartile Split			
	$PM_{2.5} \leq$ Median	$PM_{2.5} >$ Median	$PM_{2.5} \leq Q_1$	$Q_1 < PM_{2.5} \leq Q_2$	$Q_2 < PM_{2.5} \leq Q_3$	$PM_{2.5} > Q_3$
	0.001	0.049***	-0.014	0.018	0.041***	0.056***
	(0.007)	(0.007)	(0.010)	(0.023)	(0.015)	(0.010)
Model Statistics						
F-Value	52.47	94.00	64.41	10.66	18.98	87.28
# Obs.	40530	43136	20046	20484	21970	21166
Average $PM_{2.5}$	13.12	21.23	10.48	15.70	19.16	23.38
Population	113377.06	182208.82	130048.90	97019.36	120593.88	246093.54
# Municipalities	324	324	162	162	162	162

Nonlinearities: Heterogeneous effects by baseline $PM_{2.5}$