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When the Boundary Layer Drops: Air Quality and Healthcare Use in Mexico*

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We use the complete set of administrative public healthcare records in Mexico to provide the first nationwide assessment of diagnosed morbidity attributable to $PM_{2.5}$ exposure across various health conditions in a developing country. By leveraging quasi-random air pollution shocks from variations in the planetary boundary layer height across Mexican municipalities, we determine the causal impact of $PM_{2.5}$ on healthcare demand. Our findings indicate that a marginal increase in $PM_{2.5}$ leads to a 2.3% rise in emergency department admission rates. This effect varies significantly by age group and exposure levels. While most of the increase results from respiratory conditions related to air pollution, we also identify significant impacts on several previously unexplored health issues.

JEL codes: Q53, Q58, I31, I18

Keywords: Air pollution, Public health, Development, Environmental policy, Health inequality

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1. Introduction

Air pollution is the leading environmental cause of morbidity and mortality worldwide (Fuller et al., 2022). A growing body of evidence indicates that even low to moderate levels of air pollution can significant impact human health (e.g., Liu et al. 2019), with broad implications for economic outcomes. Most causal empirical research on the health effects of pollution has focused on developed countries, creating a critical gap on our understanding of these impacts across different settings (Barwick et al., 2024). Consequently, researchers often rely on dose-response relationships between pollution exposure and health outcomes estimated in the US or Europe to inform policy frameworks in low- and middle-income countries (Arceo et al., 2016). This practice raises concerns about the external validity of such benefit-transfer methods, particularly due to differences in defensive behaviors and baseline pollution levels across different contexts.

This paper provides, to our knowledge, the first nationwide causal assessment of the impact of *fine particulate matter* (PM2.5) exposure on diagnosed morbidity in a developing country. We construct a novel dataset that combines administrative healthcare records in Mexico with high-resolution satellite-based $PM_{2.5}$ pollution maps. We extract daily emergency department (ED) admission data from public hospitals using the Mexican Ministry of Health's information system and calculate municipal admission rates for all clinical diagnoses from 2008 to 2022. Mexico serves as an ideal setting for our analysis due to its universal healthcare system, which enables a representative examination of health outcomes across diverse demographic groups. About 70.9% of the population has public healthcare insurance, primarily through the *Instituto Mexicano del Seguro Social* (IMSS) and the *Instituto de Salud para el Bienestar* (INSABI) programs (INEGI, 2020). A key feature of Mexico's healthcare system is that EDs serve as a primary entry point for medical care, addressing both routine and urgent healthcare needs (OECD, 2016b). Consequently, we interpret ED admissions as a broader proxy measure of general healthcare demand in this context.

The challenges of isolating the causal relationship between pollution concentrations and health outcomes are well-documented in economics and epidemiology. A primary identification threat is endogeneity related to sorting (e.g., Chay and Greenstone, 2005; Heblich et al., 2021). To address these concerns, we use quasi-random shocks in air pollution caused by monthly variations in the height of the planetary boundary layer (PBL) across Mexican municipalities. The PBL is the lowest part of the Earth's atmosphere interacting directly with the surface. An increase in PBL height allows a greater volume of air to disperse pollution through vertical mixing, thereby reducing ground-level concentrations (Levi et al., 2020). We leverage this inverse relationship between PBL height and pollution concentrations

within a *Two-Stage Least Squares* (2SLS) framework. Our preferred specification includes flexible municipality-by-year fixed effects and month-of-the-year-by-municipality fixed effects, meaning that the identifying variation arises from deseasonalized inter-annual municipal deviations. The exclusion restriction for our instrumental variable strategy asserts that, after flexibly controlling for weather variables and municipality-specific year fixed effects, variations in PBL height do not affect local health outcomes except through their impact on air pollution concentrations.

Our empirical analysis reveals three key findings. First, our estimates show that a 1 $\mu g/m^3$ increase in $PM_{2.5}$ results in a 2.3% rise in overall admission rates. We provide evidence that this increase primarily arises from a increase in non-fatal conditions and morbidity, rather than mortality. Our calculations suggest that lowering Mexico's $PM_{2.5}$ to the *World Health Organization* (WHO) annual standard of 10 $\mu g/m^3$ could reduce annual healthcare expenditures by at least 0.5%. This reduction exceeds the estimated decline in hospitalization costs from Deryugina et al. (2019) for a comparable $PM_{2.5}$ reduction in the US (0.25%) but is lower than the estimate from Barwick et al. (2024) for $PM_{2.5}$ reductions to meet WHO limits in China (1.5%). Our findings challenge the notion that morbidity constitutes a minor aspect of the overall health burden of pollution (e.g., WHO and OECD 2015).

Second, we show that the estimated effect varies significantly by age group and primarily relates to respiratory conditions and other unexplored health issues. Our estimates reveal a U-shaped pattern across age groups, with the strongest impacts observed in pediatric and elderly patients. Moreover, we do not reject the hypothesis that these effects extend beyond the traditionally studied respiratory and cardiovascular conditions (e.g., Ward 2015; Deschenes et al. 2017). Consequently, previous estimates that focus solely on these conditions may underestimate the overall health burden of pollution exposure (e.g., OECD 2016a).

Third, we present evidence of the nonlinear nature of the dose-response function, indicating that the estimated effects primarily arise from municipalities with higher baseline $PM_{2.5}$. This finding underscores potential biases when applying dose-response functions from high-income countries to estimate mortality or morbidity benefits from reduced pollution in developing countries, which frequently experience higher levels of air pollution (Lelieveld et al., 2015).

Related literature: A substantial body of research confirms that ambient air pollution, especially fine particulate matter ($PM_{2.5}$), poses a serious threat to public health and incurs significant economic costs (Chay and Greenstone, 2003; Currie and Neidell, 2005; Currie and Walker, 2011; Ebenstein et al., 2017; Wu et al., 2020; Sarmiento, 2023). The WHO estimates that air pollution causes approximately 7 million premature deaths annually (World Health Organization, 2014), making it the largest environmental health risk worldwide. In addition

to mortality, pollution leads to significant morbidity: short-term spikes in $PM_{2.5}$ correlate with increased hospital and emergency department admissions for cardiac and respiratory conditions, acute bronchitis, asthma attacks, and other symptoms (California Air Resources Board, 2021). These health impacts create substantial economic burdens. For instance, pollution-related diseases and premature deaths cost the European economy an estimated $1.6 trillion annually (WHO and OECD, 2015), with global welfare losses from ambient air pollution reaching approximately $5 trillion.

Despite the broad consensus on the dangers of air pollution, important gaps and limitations persist in the literature. First, much of the empirical evidence, especially causal analyses, comes from high-income countries with relatively low pollution levels. Seminal studies have developed quasi-experimental strategies to estimate the health effects of pollution in the United States and Europe. Previous research has employed various plausibly exogenous sources of pollution variation, such as economic recessions (Chay and Greenstone, 2003), airport congestion (Schlenker and Walker, 2016), changes in boat traffic (Moretti and Neidell, 2011), local traffic and public transport strikes (Knittel et al., 2016; Giaccherini et al., 2021), and extreme natural events like sandstorms or volcanic eruptions (Halliday et al., 2019). Researchers have also considered atmospheric phenomena, such as wind patterns (Deryugina et al., 2019; Balietti et al., 2022) and thermal inversions (Arceo et al., 2016; Graff Zivin et al., 2023) to identify effects. However, the external validity of their estimates for developing countries remains unclear. Pollution concentrations in low- and middle-income countries often significantly exceed those in high-income nations, and the dose–response relationship may be non-linear (Deryugina et al., 2019). As Arceo et al. (2016) argues, health responses estimated at relatively low PM levels in the U.S. may underestimate damages in regions where pollution frequently reaches much higher peaks. Moreover, people in developing contexts may exhibit different defensive behaviors—such as inadequate housing insulation—and baseline health statuses that can exacerbate the effects of pollution.

A second gap in the literature is its focus on the mortality impacts of pollution, which limits our understanding of its morbidity effects. Many influential studies prioritize infant survival and senior citizen mortality because deaths are easily measured and represent the most severe consequences of exposure (Deryugina et al., 2019; Anderson, 2020). In contrast, few studies examine non-fatal health effects—such as acute illnesses requiring urgent care—particularly in younger or working-age populations (e.g., Deschenes et al., 2017). This gap partly arises from data limitations: tracking pollution-related sickness in large populations is challenging, especially in developing countries with limited data collection infrastructure (Landrigan et al., 2018). Morbidity outcomes include a range of endpoints such as acute and chronic conditions, as well as complications for individuals with preexisting health issues (Klauber

et al., 2024; Barwick et al., 2024). While these pollution-related conditions may not be fatal, they can result in significant hospitalizations and public health costs (e.g., He et al., 2019). In summary, we lack a complete understanding of how air pollution affects health across the age and morbidity spectrum in developing countries, as existing estimates may not fully capture the true burden on healthcare systems under higher pollution regimes or different populations behaviors than in high-income countries.

Contribution: Our study contributes to the literature on several ways. Methodologically, we implement a novel quasi-experimental design to identify pollution's impact on healthcare demand. We exploit plausibly random atmospheric fluctuations in PBL height that cause sharp, transient changes in local $PM_{2.5}$ concentrations (International Growth Centre, 2016). This natural experiment allows us to isolate exogenous pollution shocks from confounding factors, such as economic activity or systematic avoidance behavior, thereby addressing endogeneity challenges documented in prior work (Deryugina et al., 2019). Our approach builds on the innovative strategies of earlier studies using health microdata but, to our knowledge, it is the first applied nationwide in a developing country context. We select a continuous *instrumental variable* (IV) to address concerns about inflated estimates caused by the low statistical power associated with low-frequency event instruments (Bagilet and Zabrocki-Hallak, 2022). Experimental and cohort studies in developing countries often face ethical concerns, logistical challenges, and limited scalability. Our observational approach provides instead a modeling framework that combines real-world and satellite-based data to capture a more representative spectrum of exposure-health relationships, offering broader applicability and policy relevance.

Geographically, our analysis focuses on Mexico, providing rare evidence from the developing world. Previous studies in Mexico and other developing countries have typically focused on specific cities or infant mortality (Arceo et al., 2016; Imelda, 2020; Balietti et al., 2022). In contrast, we present the first causal estimates of $PM_{2.5}$ effects on morbidity across all ages and regions in an emerging economy. This approach fills the external validity gap by testing whether findings from U.S. and European settings apply under different environmental and institutional conditions. Unlike Barwick et al. (2024) who uses credit card transactions to estimate pollution-induced healthcare costs in China, we directly observe health outcomes, patients' demographic profiles, and diagnoses. This allows us to link $PM_{2.5}$ shocks to diagnosed morbidity and analyze effects on different populations. Additionally, Mexico offers an ideal setting to test for nonlinearities, as it experiences pollution levels typical of many developing countries. Yet, due to significant variability in pollution levels, its range also includes values comparable to those observed in the US. Finally, our findings broaden the understanding of pollution's impacts on morbidity. We show that even marginal increases in

$PM_{2.5}$ raise emergency department visits, resulting in a few percent increase in admissions. This effect size is economically significant, indicating a considerable additional burden on hospitals during polluted periods.

Importantly, we document heterogeneity across health conditions and demographic groups. The pollution-induced surges in emergency room demand are driven largely by respiratory emergencies (e.g., acute exacerbations of asthma and chronic obstructive pulmonary disease), which aligns with medical evidence linking particulates to cardiopulmonary problems. However, we also identify increases in previously under-studied acute conditions not typically associated with pollution exposure, suggesting a broader range of health vulnerabilities. Moreover, the impact differs by age group: as expected, young children and the elderly experience the largest increases in emergency visits when air quality deteriorates, reflecting their greater susceptibility, while working-age adults show more moderate responses (Deryugina et al., 2019). By quantifying these differential effects, our study sheds light on the distributional consequences of air pollution in a developing country, a key area of research where evidence remains scarce (Drupp et al., 2025). Our results demonstrate that the health costs of pollution extend beyond mortality into significant short-run demands on healthcare systems and that these costs are unevenly borne across the population. These quasi-experimental findings help bridge the gap between developed- and developing-country evidence and offer relevant insights for environmental policy and public health planning in emerging economies.

2. Data

Air pollution. We utilize representative $PM_{2.5}$ estimates from remote sensing to assess the impact of air pollution variations on emergency room admissions (Van Donkelaar et al., 2021). The $PM_{2.5}$ data consists of 0.01 by 0.01 degree gridded monthly $PM_{2.5}$ estimates from 1998 to 2022. Each gridded value integrates aerosol optical depth data from the *North American Space Agency* (NASA) with a chemical transport model and geographically weighted regressions. After obtaining the $PM_{2.5}$ data, we aggregate it into monthly population-weighted averages for each municipality across the country. For this, we use data from the *Gridded Population of the World raster* (GPWv4) provided by NASA's Center for Socioeconomic Data and Applications. GPWv4 offers spatially resolved population estimates with a resolution of 30 arc seconds (i.e., approximately 1 km at the equator).

Weather. Weather conditions significantly influence air pollution and health status. We combine $PM_{2.5}$ data with weather covariates from the ERA5 dataset, a leading atmospheric reanalysis product by the *European Center for Medium-Range Weather Forecasts* (ECMWF).

This dataset provides hourly estimates of weather variables, such as air temperature, precipitation, and atmospheric pressure. We aggregate weather measures into population-weighted averages for each municipality, consistent with our treatment of $PM_{2.5}$.

Emergency room admissions. We obtain data on daily ED visits from the health information system of the Mexican health ministry. The dataset includes all emergency department visits in public hospitals across Mexico from 2008 and 2022. Each observation records a single admission and provides information on patient characteristics (age, sex, residence, insurance), event details (outcome, ICD-10 code, reason), and geographical identifiers (hospital ID, municipality, state). Using these data, we constructed a panel of daily admissions per 100,000 persons for municipalities with at least one hospital. For this, we sourced population data from the Mexican Census for 2000, 2010, and 2020. We also categorized the number of visits by sex (men and women), age (six age groups), ICD-10 code (e.g., cardiovascular, respiratory, infectious-parasitic), and outcome (death, hospitalization, home).

Table 1 presents various descriptive statistics related to our data. The average monthly admission rate is 157 cases per 100,000 people. Women have higher rates than men because many Mexican women visit the ED for routine obstetric check-ups and follow-ups. The age dynamics reveal distinct patterns. Admission rates for children under 12 exceed those for adolescents aged 12 to 20, reflecting the generally weaker immune systems of younger children. As we transition from adolescents to young adults aged 20 to 40, the rate increases by nearly 20%, primarily due to obstetric conditions. After reaching the end of their reproductive years, the rate decreases by 36% for those aged 40 to 60 but rises again in older cohorts.

Respiratory and cardiovascular diseases, often linked to air pollution, contribute significantly to hospital visits. Admissions for external causes, obstetric issues, digestive problems, and infectious diseases are also important. We present descriptive statistics on air pollution, including raw and population-weighted average values, to highlight potential variations. The average population-weighted $PM_{2.5}$ concentration is 17.29 *micrograms per cubic meter* ($\mu g/m^3$), with a standard deviation of 7.52 $\mu g/m^3$. These levels exceed the WHO's recommended daily exposure limit of 10 $\mu g/m^3$.

3. Empirical design

Our empirical strategy estimates the effect of $PM_{2.5}$ variations on monthly emergency department visits in each municipality using fixed-effects *Poisson Pseudo-Maximum Likelihood Estimator* (PPML) panel models (Wooldridge, 1999). We chose this approach because *Ordinary Least Squares* (OLS) violates the assumptions of homoskedasticity and normally dis-

tributed errors due to the count nature of the data (Chen and Roth, 2023). Equation 1 presents the econometric specification of our primary regression model.

$$ED_{ct} = \exp\left[\beta PM2.5_{ct} + \gamma X_{ct} + \delta_{cm} + \delta_{cy}\right] + \epsilon_{ct} \tag{1}$$

In this model, ED_{ct} denotes the admission rate per 100,000 people in municipality c during period t (year-month). β is the parameter of interest, measuring the marginal effect of an additional unit of $PM_{2.5}$ on the logarithm of the admission rate. X_{ct} represents a matrix of weather control variables. Our preferred specification includes five indicator variables for average temperature and precipitation. We also include fixed effects for municipality/month-of-the-year (δ_{cm}) and municipality/year of observation (δ_{cy}). This combination of fixed effects allows us to identify the coefficient from interannual changes in $PM_{2.5}$ within each municipality. We cluster standard errors at the municipal level to address correlations in unobservables within municipalities and to account for autocorrelation over time. Additionally, we weight all estimates by the population in each municipality to enhance spatial representativeness and account for heteroskedasticity.

Instrumental variable approach. As noted by Deryugina et al. (2019), a limitation of the previous model is that, despite our controls and fixed effects, the estimates of Equation 1 may remain biased. This bias arises because exposure to air pollution is not randomly assigned and is subject to measurement error. To address this issue, we employ a control function approach, which is simpler to implement with non-linear Poisson models (Lin and Wooldridge, 2019; Burkhardt et al., 2019; Klauber et al., 2020). In the first stage, we conduct an OLS estimation of the endogenous variable ($PM_{2.5}$). In the second stage, we apply the previously discussed PPMLE, using the fitted values from the first stage as the causal variable.

Following previous studies, we used the height of the planetary boundary layer (PBLH) as an instrumental variable for $PM_{2.5}$ (e.g., Godzinski and Castillo 2021; Kögel 2022). The planetary boundary layer is the lowest part of the atmosphere, directly influenced by Earth's surface. Air pollutant concentrations inversely correlate with PBLH. A low PBLH traps pollutants in a smaller air volume, leading to higher concentrations and poorer air quality. Conversely, a higher PBLH facilitates pollutant dispersion, reducing near-surface concentrations. Figure 1 presents a diagram illustrating the theoretical relationship between the planetary boundary layer and air pollution.

A potential identification threat is that pollution could affect the PBLH. As Dechezleprêtre et al. (2019), we refer to atmospheric physics literature that confirms aerosols can reduce

the PBLH by reflecting sunlight. However, modeling evidence suggests this effect occurs only at extremely high baseline pollution levels—approximately 30 times the sample average—combined with a significant pollution shock around 5 times the standard deviation of our sample (Petäjä et al., 2016). In our empirical setting, we can reasonably rule out reverse causality.

We chose to use variations in the height of the PBL as our instrument instead of thermal inversions or wind direction, as seen in previous research, for two main reasons. First, recent evidence suggests that using thermal inversions computed at coarse resolutions can inflate coefficient sizes due to the rarity of these events (Bagilet and Zabrocki-Hallak, 2022). Second, while wind direction does not face the same issues as thermal inversions, its first stage is often difficult to interpret because the mechanisms behind the estimated coefficients are unclear (Deryugina et al., 2019).

We construct the PBLH instrument using ERA5 gridded hourly data from ECMWF. We aggregate this data to daily levels by calculating the arithmetic mean for each day. To convert daily gridded values to municipal values, we compute the population-weighted average of all grids within each municipality. After calculating daily PBLH for each municipality, we aggregate it to the monthly level by taking a simple average of all days. Figure B.1 in the Appendix illustrates the relationship between the monthly average PBLH and $PM_{2.5}$ in our data. Consistent with the physical properties of PBLH, increasing the layer height substantially reduces average $PM_{2.5}$ levels.

One concern about using PBLH as an instrument for air pollution parallels issues observed with other weather instruments, such as wind direction and thermal inversions. Temperature variations and other weather factors can affect both PBLH and the dependent variable. For instance, during warmer periods, solar radiation heats the ground and the air above it, causing the air to rise and increasing the PBLH. Thus, while PBLH does not directly affect health, it could correlate with weather conditions that affect both air pollution and emergency room admissions (White, 2017; Gould et al., 2024). To mitigate this concern, we include various weather controls in our regression analysis. We use non-parametric indicators for temperature and precipitation, along with average values of relative humidity and atmospheric pressure in the preferred specification.

The primary assumption is that, after controlling for fixed effects and meteorological conditions, changes in PBLH act as a natural experiment that exogenously modifies individual exposure to air pollution. Equation 2 outlines the econometric strategy for the first-stage relationship between $PM_{2.5}$ and PBLH. In this equation, $PM2.5_{ct}$ represents the average value of $PM_{2.5}$ for municipality c at time t. $PBLH_{ct}$ indicates the average PBLH. The remaining

parameters correspond to Equation 1.

$$\hat{PM2.5}_{ct} = \left[\beta PBLH_{ct} + \gamma X_{ct} + \delta_{cm} + \delta_{cy} + \epsilon_{ct}\right]\omega_{ct} \tag{2}$$

After estimating $\hat{PM2.5}_{ct}$, we use it as the dependent variable in the second stage of the control function approach (I.e.,Equation 3). We apply bootstrapped nonparametric standard errors, clustered at the municipal level, to address the use of fitted values instead of actual PM2.5 in the econometric design (Lin and Wooldridge, 2019).

$$ER_{ct} = \omega_{ct} \times \left[\exp\left(\beta \hat{PM2.5}_{ct} + \gamma X_{ct} + \delta_{cm} + \delta_{cy}\right) + \epsilon_{ct}\right] \tag{3}$$

4. Results

Baseline. Table C.3 presents point estimates from the control function approach for the general population. We provide results for three specifications. (1) includes fixed effects for the municipality to control for cross-sectional differences in $PM_{2.5}$ levels and mortality rates. (2) adds weather controls along with fixed effects for the year and month of observation. Weather controls are crucial as they affect admission rates, air pollution, and our instrument. We account for temperature non-linearly using six intervals ranging from 10°C or below to over 35°C, with 20°C and 25°C as the reference interval. For precipitation, we include five variables representing the number of days per month when precipitation volumes fall within each quintile of the municipal value distribution. We also include average values for relative humidity and atmospheric pressure. The fixed effects for year and month account for common shocks impacting all municipalities, like changes in social security access or seasonal influenza (Graff Zivin et al., 2023). (3) captures municipal seasonality and yearly shocks with more nuanced fixed effects, such as municipality-specific month-of-the-year and municipality-by-year fixed effects.

The results are statistically significant across all specifications. They indicate that emergency room admission rates increase by 0.4% to 2.3% with each additional μgm^3. We select the third specification as our preferred model. Using the average admission rate, the 2.3% increase corresponds to 3.8 additional monthly admissions per 100,000 people. With an average population of 148,000, this marginal effect results in 5.6 additional monthly patients requiring emergency services per municipality for each additional $\mu g/m^3$ of $PM_{2.5}$. Table C.4 in the Appendix shows that the estimated effect results from an increase in non-fatal conditions

and morbidity rather than mortality.

We estimate lower-bound monetary values for increased admissions using cost data from the Mexican Health Ministry, which reports material and labor costs per admission at 4,200 MXP (Instituto Mexicano del Seguro Social, 2023). We supplement this figure with the average daily wage of a Mexican worker, approximately 260 MXP, as a proxy for the marginal cost of labor (OECD, 2016c).[1] Based on the admission cost, this totals 114.3 million MXP, or about 14 million USD. Assuming each admission results in a loss of one average workday, we add an additional 870,000 USD, leading to total costs of nearly 15 million USD per month, or approximately 180 million USD per year. This amount represents about 0.5% of Mexico's annual healthcare expenditure.[2]

We can compare our findings with existing literature on the impact of air pollution on health in the United States to clarify the magnitude of our estimations. Deryugina et al. (2019) find that a 1 $\mu g/m^3$ increase in $PM_{2.5}$ leads to an additional 0.69 deaths and 2.05 ED visits per million elderly over three days. This increase corresponds to a 0.17% rise in mortality and a 0.11% rise in ED admission rates. To compare these estimates with our findings, we divide a 30-day month into 10 independent three-day periods, assuming a simple linear and non-overlapping combination of point estimates. Extrapolating the three-day coefficients to monthly values yields an approximate 1.1% increase in ED admission rates per month. Assuming full additivity, where daily exposure contributes an independent 0.33% increase, the monthly impact could reach 3.3%. Our point estimates, which aggregate exposures and outcomes at the monthly level, fall between these two values.

In terms of medical expenses, Deryugina et al. (2019) indicates that a 4.9 $\mu g/m^3$ reduction in $PM_{2.5}$ in the US leads to approximately 1.5 billion USD in annual hospitalization cost savings. This scales to about 2.3 billion USD for a comparable 7.5 $\mu g/m^3$ reduction. This linear interpolation allows us to compare this estimate to our calculations for Mexico. With total US healthcare expenditures of 0.92 trillion USD, a 7.5 $\mu g/m^3$ reduction in $PM_{2.5}$ cor-

[1] We estimate this value from the average monthly wage in the National Survey of Employment and Occupation for the third trimester 2024 (Secretaría de Economía, Gobierno de México, 2024). This value is equivalent to 8,200 pesos or about 260 MXP per day. Including wages in these calculations assumes that all people admitted to the ED are workers. We defend this assumption using previous evidence that even if they are not actively working, family members will likely lose a workday because of care. For instance, Aragon et al. (2016) find evidence of significant labor supply shocks associated with PM2.5 occur through the care channel. Moreover, the additional cost of losing one work day represents less than 10% of our back-of-the-envelope calculation.

[2] Cost estimates have been converted from MXP to USD using a 2015 PPP-adjusted exchange rate of 8.1 MXN per dollar, as per the International Monetary Fund. Data on healthcare expenditures have been retrieved from OECD Health Statistics. Here, we used Mexico's annual real healthcare expenditures in 2015, which amounted to 36.667 billion USD (PPP-adjusted).

responds to an estimated 0.25% decrease in healthcare spending.[3] The larger percentage reduction in healthcare spending in Mexico (0.5%) compared to the U.S. (0.25%) suggests that health-related costs of air pollution have a more significant impact on Mexico's healthcare costs. That is, despite the absolute reductions are lower, the relative impact on the country's healthcare budget is notably higher, indicating a greater relative opportunity cost in healthcare fund allocation.

Heterogeneous effects by demographic groups. Table 4 presents heterogeneous treatment effects by age group and sex. The effects by age group form a U-shaped curve. The largest impact occurs in children under 12, reflecting a 4.7% increase in the admission rate. The next highest effects are observed in individuals over 80 (3.1%), those aged 12 to 20 (2.6%), 60 to 80 (1.7%), and 20 to 40 (1.4%). Marginal effects are important; however, converting rates into patient counts is essential for assessing the impact on service demand. This conversion indicates an increase of 2.8 pediatric patients, 1 adolescent, 1.2 young adults, approximately 0.4 persons aged 60 and 80, and 2 individuals over 80 per municipality per month. Analysis by sex reveals slightly greater effects for men. The marginal effect indicates a 2.5% increase for men and a 2.2% increase for women. However, this difference lacks statistical significance and requires cautious interpretation. Converting the relative increase into patient counts implies an increase of 3.5 women and 2.3 men seeking ED services.

Heterogeneous effects by health conditions. Most literature on the health effects of air pollution examines its impact on respiratory and cardiovascular diseases (RCV). This emphasis arises from robust epidemiological evidence linking exposure and RCV conditions (Pope et al., 2002; Brook et al., 2010). However, concentrating solely on RCV may overlook other mechanisms through which $PM_{2.5}$ influences the demand for emergency room services. These include exacerbating pre-existing conditions by increasing strain on the body (Klauber et al., 2024), promoting violence (Bondy et al., 2020), or causing traffic-related accidents (Sager, 2019). Table 3 estimates the effect of $PM_{2.5}$ on RCV and other conditions separately to identify potential impacts on diseases beyond RCV.

In line with the epidemiological literature, the effect on RCV significantly exceeds the general impact. An additional unit of $PM_{2.5}$ increases the RCV admission rate by 7.9%, leading to 4.4 more patients in the emergency department. Non-RCV conditions also show a positive and statistically significant effect, though smaller. This effect leads to a 1.2% increase in conditions unrelated to the respiratory or cardiovascular systems, averaging 2.4 additional patients per month per municipality.

Table C.1 of the Appendix presents results for each ICD-10 chapter. We estimate increases in

[3]For this calculation, we used US annual real healthcare expenditures in 2013 from OECD Health Statistics.

respiratory diseases (9.1%), eye and ear conditions (2.8%), abnormal clinical findings (2.3%), infectious diseases (1.7%), external causes (1.1%), and other unclassified conditions (1.4%). For the remaining chapters, we observe positive coefficients, except for mental and behavioral admissions. However, these coefficients lack statistical significance at conventional levels.[4]

Nonlinear impacts of air pollution. Table 5 presents heterogeneous effects based on varying exposure levels, using both a median and quartile split of municipal average $PM_{2.5}$. The first two columns highlight a clear contrast between municipalities with $PM_{2.5}$ levels below and above the median (13.12 $\mu g/m^3$). A quasi-random shock in $PM_{2.5}$ has a negligible effect on municipalities with lower pollution levels (0.1%) but a significant positive effect on those with higher pollution levels (4.9%). This finding suggests that the ED admission rate is more sensitive to increases in $PM_{2.5}$ in municipalities with higher baseline pollution. Analyzing the quartile split reveals further details. The effect progressively increases with higher $PM_{2.5}$ concentrations. For municipalities with low $PM_{2.5}$ exposure (first quartile, $\leq$ 10.48 $\mu g/m^3$), we do not observe an statistically significant relationship. As baseline pollution levels rise, the estimated effect of a pollution shock becomes positive and increases in magnitude. Municipalities in the second quartile ($10.48 < PM_{2.5} \leq 15.70$ $\mu g/m^3$) experience a moderate increase in admissions (1.8%), though this is not statistically significant. In contrast, those in the third quartile ($15.70 < PM_{2.5} \leq 19.16$ $\mu g/m^3$) show a stronger, statistically significant effect (4.1%). The effect continues to rise in the highest exposure group ($PM_{2.5}$ > 23.38 $\mu g/m^3$), reaching a 5.6% increase in admissions. However, the rate of increase slows compared to the change between the second and third quartiles. This suggests that beyond a certain threshold, the additional health burden per $\mu g/m^3$ increase in $PM_{2.5}$ may grow at a decreasing rate, possibly due to nonlinear physiological responses or adaptation effects.

Our findings suggest diminishing marginal effects that plateau beyond certain thresholds. This contrasts with recent evidence from China, which shows a linear relationship between pollution and health effects (Barwick et al., 2024). These differences can arise from the heterogeneous distribution of pollution levels in China and Mexico. While pollution levels in China average 56.33 $\mu g/m^3$, our setting encompasses a broader range of lower pollution levels, where nonlinear effects are more evident. At higher pollution concentrations, as seen in China, the relationship may appear more linear, potentially explaining the differences between our findings and (Barwick et al., 2024).

[4]When correcting for multiple hypothesis testing, only respiratory diseases and eye–ear conditions remain statistically significant. Yet, given the robustness of our model—which utilizes strong instruments and high-dimensional fixed effects to control for unobserved confounders—we contend that the unadjusted p-values may be more reliable. In our case, the high correlation between ICD-10 chapters implies that standard corrections like the Bonferroni method may underestimate the true relevance of some effects (Rothman, 1990; Perneger, 1998) .

5. Discussion

Research in epidemiology and economics has long examined the health effects of air pollution, particularly its impact on mortality. However, most studies focus on high-income nations. This study addresses this gap by utilizing administrative public healthcare records from Mexico, providing a first nationwide assessment of diagnosed morbidity due to $PM_{2.5}$ exposure in a non-high-income country. To address endogeneity concerns, we exploit quasi-random air pollution shocks caused by variations in the height of the planetary boundary layer across Mexican municipalities.

Our analysis shows that a 1 $\mu g/m^3$ increase in PM2.5 leads to a 2.3% rise in emergency department visits, primarily due to an increase in non-fatal diagnoses. The estimated effect varies by age, with the strongest impacts observed on children and the elderly. We document a nonlinear dose-response relationship, indicating stronger effects in municipalities with higher baseline pollution levels. This raises concerns about extrapolating estimates from high-income countries, which typically have lower air pollution levels, to other contexts (Lelieveld et al., 2015). We provide back-of-the-envelope calculations suggesting that compliance with the WHO annual PM standard could save approximately 180 million USD per year, or about 0.5% of annual health expenditures. This highlights a significant opportunity cost in healthcare resource allocation and underscores the economic burden pollution imposes on public funds.

More generally, our results show that neglecting the economic burden of morbidity can significantly underestimate the overall economic costs of pollution, consistent with recent evidence from Barwick et al. (2024). Additionally, we show that these impacts extend beyond the respiratory and cardiovascular diseases typically considered in previous studies (e.g., Deschenes et al. 2017). However, these estimates represent only a lower bound of potential benefits from pollution reduction. Prior literature suggests that air pollution also affects additional dimensions not captured in our analysis, such as mortality (Deryugina et al., 2019), productivity (Chang et al., 2019; Sarmiento, 2022; Leroutier and Ollivier, 2025), labor supply (Hoffmann and Rud, 2024; Hanna and Oliva, 2015), private defensive behavior (Ito and Zhang, 2020), road accidents (Sager, 2019) and violence (Bondy et al., 2020; Sarmiento, 2023). Furthermore, limited healthcare access in Mexico may lead to an underestimation of effects, as some morbidity may go unrecorded in healthcare utilization data (Gutiérrez et al., 2014).

Our findings have important policy implications. First, using average dose-response functions from high-income countries with lower pollution levels for cost-benefit evaluations likely misguides policy prioritization and resource allocation in low- and middle-income economies (Muller and Mendelsohn, 2009). Moreover, we show that the morbidity impacts of air pol-

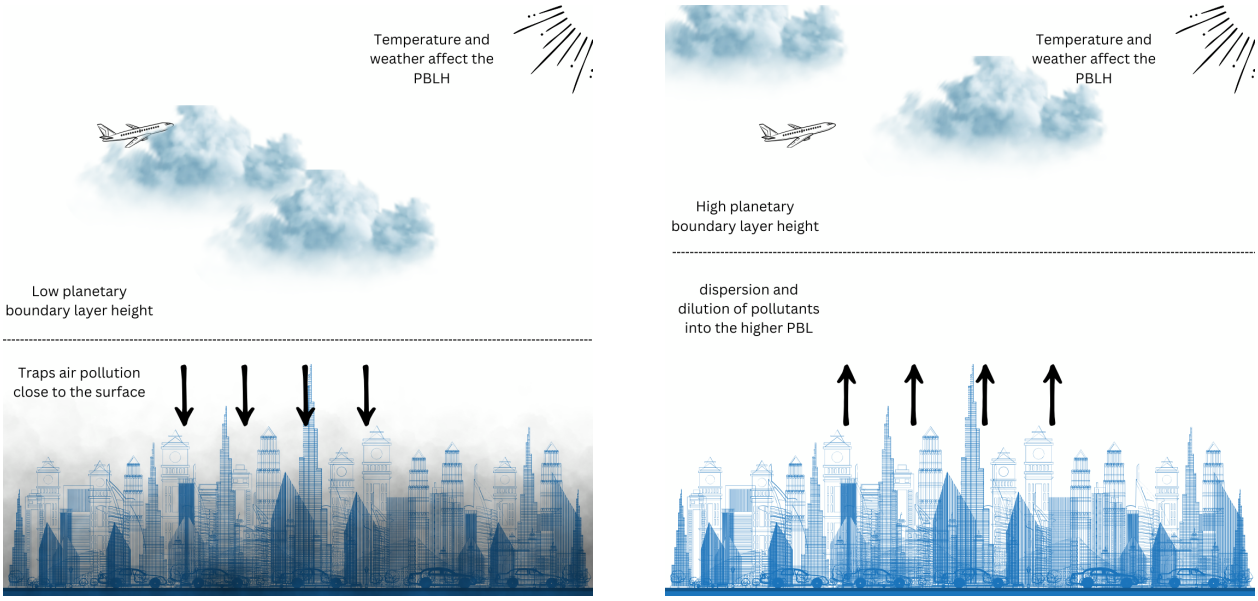
lution are unevenly distributed, with the most severe effects concentrated in municipalities with higher baseline pollution. These environmental inequalities can worsen existing economic disparities, as disadvantaged populations often live in more polluted areas (Colmer et al., 2020, 2024; Sager, 2025). Poor air quality not only increases healthcare expenditures but also hinders human capital accumulation, potentially creating pollution-income traps (Drupp et al., 2025). Policymakers should account for these differential effects when designing local pollution reduction strategies to ensure both efficiency and equity. This may involve incorporating distributional weights into environmental policy assessments, as suggested in the literature (e.g., Adler 2016).

Second, we show that the morbidity impacts of air pollution may represent a significant portion of overall healthcare costs. Our results suggest that the non-linear increase in admissions during periods of high pollution could overwhelm public hospitals, especially in resource-limited settings. Investing in nationwide public education campaigns and pollution alerts can produce substantial health benefits at relatively low costs. These campaigns enable individuals to adopt protective measures, such as reducing outdoor exposure during high-pollution periods. Increasing awareness of pollution's health effects can also foster public support for stricter environmental regulations. Finally, our findings are relevant for evaluating national climate policy scenarios and their distributional effects in Mexico. While carbon abatement policies do not directly target air pollutants, they can significant improve air quality by reducing emissions of toxic co-pollutants (Hernandez-Cortes and Meng, 2023; Basaglia et al., 2024; Loughlin et al., 2024). To accurately account for these benefits (and their distribution) in cost-benefit analyses, context-specific pollution damage estimates are essential. Further research is urgently needed to understand the complex dynamics of air pollution and public health, especially in developing countries. A promising approach involves monitoring individuals' exposure to outdoor *and* indoor pollution throughout the day to assess their differential impacts on health outcomes (e.g., Metcalfe and Roth 2025).

Table 1: Summary Statistics

	Average	Standard Deviation	Maximum	Minimum	Units
Admission Rates					
General	157.31	188.26	4273.71	0.00	per 100,000 people
Male	117.74	151.43	3332.14	0.00	per 100,000 people
Female	194.78	228.96	5172.77	0.00	per 100,000 people
Age 0-12	166.03	232.06	4367.28	0.00	per 100,000 people
Age 12-20	152.22	181.13	4395.47	0.00	per 100,000 people
Age 20-40	183.55	215.80	5208.89	0.00	per 100,000 people
Age 40-60	116.33	160.36	3044.87	0.00	per 100,000 people
Age 60-80	148.93	216.60	3746.16	0.00	per 100,000 people
Age 80-130	224.57	332.84	6698.20	0.00	per 100,000 people
Population	148,841	25,594	198,560	1,037	#
Main conditions					
Respiratory/Cardiovascular	34.45	49.12	1035.16	0.00	per 100,000 people
External Causes	25.46	31.23	871.54	0.00	per 100,000 people
Obstetric	14.03	24.20	596.09	0.00	per 100,000 people
Digestive	12.55	15.41	327.27	0.00	per 100,000 people
Infectious	12.50	20.55	810.19	0.00	per 100,000 people
Abnormal Clinical Findings	11.79	18.75	730.69	0.00	per 100,000 people
Eye/Ear	2.83	4.88	129.26	0.00	per 100,000 people
Rest of Conditions	49.73	65.32	1336.04	0.00	per 100,000 people
Main outcome					
Patient sent home	133.31	169.35	3745.18	0.00	per 100,000 people
Hospitalization	20.05	31.66	969.64	0.00	per 100,000 people
Death	0.17	2.25	422.33	0.00	per 100,000 people
Unspecified	3.76	18.75	1477.83	0.00	per 100,000 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					
$PM_{2.5}$	16.46	7.58	121.64	1.52	μgm^3
$PM_{2.5}$ Weighted	17.29	7.52	102.83	2.02	μgm^3

Notes: Self constructed values using aggregated data from the Health Information System of the Mexican Health Ministry, ECMWF, and Van Donkelaar et al. (2021).



a) Low PBLH conditions b) High PBLH conditions

Figure 1: The planetary boundary layer highet and air pollution

Table 2: Marginal Effect of $PM_{2.5}$ on ED Admission Rates

	(1)	(2)	(3)
Second stage β from Eq. 3			
$PM_{2.5}$ ($\mu g/m^3$)	0.004***	0.008***	0.023***
	(0.002)	(0.002)	(0.006)
Model Statistics			
Observations	84,034	84,034	83,666
Municipalities	648	648	648
F-statistic (first stage)	71.74	101.12	100.33
Mean admission rate (per 10k)	167.59	167.59	167.59
Avg. municipal population	148,793	148,793	148,793
Fixed Effects			
Municipality	✓	✓	✓
Year		✓	✓
Month		✓	✓
Municipality × month-of-year			✓
Municipality × year			✓
Controls			
Weather variables		✓	✓

Notes: This table presents point estimates from a control function Poisson MLE regression of municipal emergency department (ED) admission rates per 100,000 people in Mexico on instrumented $PM_{2.5}$. We instrument municipal population-weighted $PM_{2.5}$ using the average planetary boundary layer height in the municipality. Weather controls include indicators for days within five temperature bins (10-30°C), precipitation quintiles, relative humidity, and atmospheric pressure. Standard errors are clustered at the municipality level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Marginal effect of $PM_{2.5}$ on emergency department admission rates: Heteogeneous effects between RCV and non-RCV conditions

	General Effect	RCV	Non-RCV
Second stage β from Eq. 3			
$PM_{2.5}$ ($\mu g/m^3$)	0.023***	0.079***	0.012**
	(0.006)	(0.009)	(0.006)
Model Statistics			
Observations	83666	79578	80237
F-statistic (first stage)	100.328	110.714	110.714
Mean admission rate (per 10k)	167.9	37.9	137.5
Avg. municipal population	148.793	148.793	148.793
Fixed Effects			
Municipality × month-of-the-year	✓	✓	✓
Municipality × year	✓	✓	✓
Controls			
Weather variables	✓	✓	✓

Notes: This table presents the point estimates of a control function approach Poisson MLE of municipal emergency department admission rates per 100,000 people in Mexico as a function of instrumented $PM_{2.5}$. We present results separatelly for the general admission rate and for the admission rate for respiratory-cardiovascular (RCV) and non-RCV conditions. We instrument municipal population-weighted $PM_{2.5}$ with the average planetary boundary layer height in the municipality. All columns control for municipality-by-year and municipality-by-month fixed effects along with weather controls including five indicator variables for the number of days per month between 10 and 30 degrees Celsius in five-degree intervals, indicator variables for the within municipality quintile of daily precipitation, relative humidity and atmospheric pressure. Standard errors are clustered at the municipality level. Significance codes: *** < 0.01,** < 0.05,* < 0.1.

Table 4: Marginal effect of $PM_{2.5}$ on emergency department admission rates: Heterogeneous effects by age group and sex

	Age Groups						Sex	
	0-12	12-20	20-40	40-60	60-80	80-130	Female	Male
Second stage β from Eq. 3								
$PM_{2.5}$ ($\mu g/m^3$)	0.047***	0.026***	0.014***	0.008	0.017**	0.031***	0.022***	0.025***
	(0.008)	(0.006)	(0.006)	(0.006)	(0.007)	(0.008)	(0.005)	(0.006)
Model Statistics								
Observations	83255	83408	83197	83016	82480	82008	83533	83368
Municipalities	648	648	648	648	648	648	648	648
F.Stat (first stage)	85.851	91.088	94.664	110.459	131.677	133.069	101.887	98.658
Avg. municipal population	31.526	21.604	47.084	32.691	13.599	2.289	76.463	72.331
Mean admission rate (per 10k)	180.7	160.9	193.2	123.1	159.1	243.1	207.6	125.5
Fixed Effects								
Municipality by month-of-the-year	✓	✓	✓	✓	✓	✓	✓	✓
Municipality by year	✓	✓	✓	✓	✓	✓	✓	✓
Controls								
Weather controls	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table presents the point estimates of a control function approach Poisson MLE of municipal emergency department admission rates per 10,000 people in Mexico as a function of instrumented $PM_{2.5}$. We present results for six different age categories, females, and males seperately. We instrument municipal population-weighted $PM_{2.5}$ with the average planetary boundary layer height in the municipality. Weather controls include five indicator variables for the number of days per month between 10 and 30 degrees Celsius in five-degree intervals, indicator variables for the within municipality quintile of daily precipitation, relative humidity and atmospheric pressure. Standard errors are clustered at the municipality level. Significance codes: *** < 0.01,** < 0.05,* < 0.1.

Table 5: Marginal effect of $PM_{2.5}$ on emergency department admission rates: Heterogeneous effects by $PM_{2.5}$ average exposure levels

	Median Split		Quartile Split			
	$PM_{2.5} \leq$ M1	$PM_{2.5} >$ M1	$PM_{2.5} \leq Q_1$	$Q_1 < PM_{2.5} \leq Q_2$	$Q_2 < PM_{2.5} \leq Q_3$	$PM_{2.5} > Q_3$
Second stage β from Eq. 3						
$PM_{2.5}$ ($\mu g/m^3$)	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						
Observations	40530	43136	20046	20484	21970	21166
Municipalities	324	324	162	162	162	162
F.Stat (first stage)	52.47	94.00	64.41	10.66	18.98	87.28
Average $PM_{2.5}$	13.12	21.23	10.48	15.70	19.16	23.38
Mean admission rate (per 10k)	189.2	147.2	171.8	206.2	169.6	124.0
Avg. municipal population	113377.06	182208.82	130048.90	97019.36	120593.88	246093.54
Fixed Effects						
Municipality × month-of-the-year	✓	✓	✓	✓	✓	✓
Municipality × year	✓	✓	✓	✓	✓	✓
Controls						
Weather variables	✓	✓	✓	✓	✓	✓

Notes: This table presents the point estimates of a control function approach Poisson MLE of municipal emergency department admission rates per 100,000 people in Mexico as a function of instrumented $PM_{2.5}$. We instrument municipal population-weighted $PM_{2.5}$ with the average planetary boundary layer height in the municipality. We present estimates for six different sample splits based on the average municipal $PM_{2.5}$. The first two columns estimates the effect for municipalities below and above the median $PM_{2.5}$. The next four columns make the split using quartiles. Standard errors are clustered at the municipality level. Significance codes: $^{***} < 0.01$,$^{**} < 0.05$,$^{*} < 0.1$.

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Appendix A The Mexican health-care system.

Mexico's healthcare system combines public and private components, akin to other middle-income countries like Brazil, Argentina, Colombia, and South Africa. Public institutions primarily serve formal workers and their dependents. In addition, the Institute of Health for Well-being (INSABI), which replaced the *Seguro Popular* program, provides care for the uninsured. This public system coexists with a robust private sector that offers high-quality services. However, these services tend and be more expensive and are mainly accessible to those with private insurance or sufficient financial resources.

Coverage statistics highlight the system's heterogeneity. Public social security for formal workers insures roughly 45% of the population, INSABI covers about 30%, and private insurance accounts for only 2.4%. Despite INSABI's goal of universal coverage, 20% of Mexicans reported lacking access to healthcare in 2020. This shortfall contrasts with the United States, where two-thirds of individuals rely on private insurance, roughly one-quarter benefits from public programs like Medicare or Medicaid, and around 9% remain uninsured. In Mexico, individuals without formal insurance can access public sector options for a low fee or choose private sector services at a higher cost.

When compared to other OECD countries, Mexico's healthcare model exhibits unique financing and access dynamics. Unlike the predominantly privatized U.S. approach, which relies heavily on employer-based coverage and out-of-pocket spending, Mexico aims to broaden public sector coverage. However, it still faces challenges related to funding and equity. In contrast, European single-payer systems, such as those in the United Kingdom and Sweden, are primarily tax-funded, providing near-universal coverage with minimal out-of-pocket expenses. Importantly, Mexico's low healthcare expenditure as a percentage of GDP, combined with a decentralized public-private mix, presents significant challenges in delivering comprehensive and equitable care comparable to many European nations.

Recent government initiatives have attempted to consolidate and reorient the system. While reforms under former administrations—such as the creation of Seguro Popular—expanded access dramatically, subsequent restructuring under President Andrés Manuel López Obrador aimed to recentralize and streamline services through INSABI. However, challenges in funding, bureaucratic inefficiencies, and persistent resource constraints have limited the effectiveness of these reforms. For instance, shortages of essential supplies and medications, exacerbated by issues in procurement and distribution, have repeatedly strained both public and private institutions, leading to periodic crises in service delivery

Note that the absence of a system for registering with a designated primary care physician

and limited opening hours foster a reliance in episodic care, leading patients to frequently utilize hospital emergency departments (ED). For instance, the most common reason for ED visits in Mexico is ICD-10 code Z34, for *supervision of normal pregnancy*. Additionally, 85% of ED patients are discharged after their first visit, indicating that our analysis extends beyond critical condition treatments. Of the remaining 15%, 12.5% are hospitalized, 0.2% die, and 2.3% have unknown outcomes. While ED visits serve as a proxy for healthcare demand, they exclude visits to family doctors, pharmacies, or other healthcare services. We interpret our analysis as providing a lower-bound estimate of pollution-induced morbidity costs. See the Online Appendix for an overview of Mexico's healthcare system.

Appendix B Data

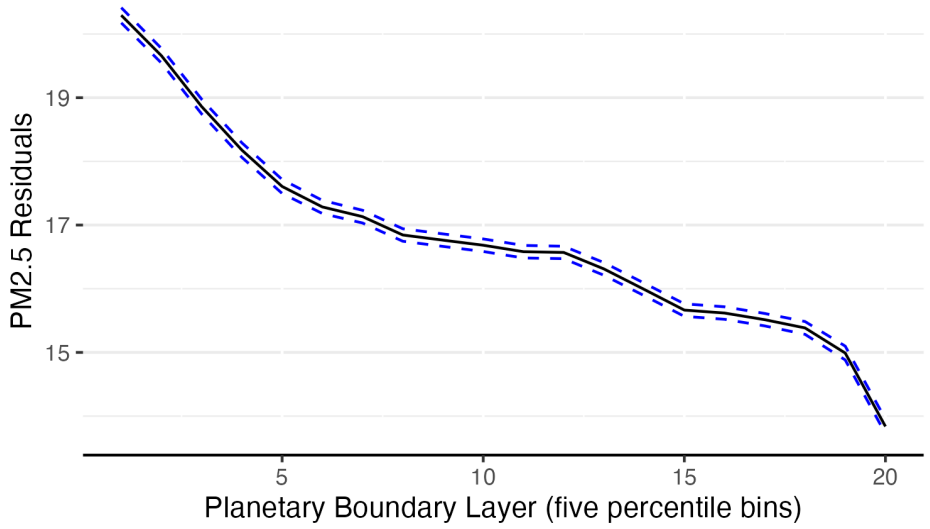

Figure B.1: Average $PM_{2.5}$ vs PBLH

Notes: We generated the figure by dividing PBLH into five percentile intervals and estimating the average $PM_{2.5}$ for each municipality. This method directly assesses the $PM_{2.5}$ difference across various PBLH values within municipalities. The difference between the lowest and highest five-percentile intervals is 32%.

Appendix C Results

Table C.1: Point estimates by ICD-10 chapter

ICD-10 Code	Estimate	F-Value	#Obs	PR2	Cor2	MRate	Pop	$PM_{2.5}$	P-Value BH
Respiratory	0.0911***	100.33	82507	1.02	0.88	30.7	148793.06	17.29	0.0000
	(0.0107)								
Eye and ear	0.0286***	110.71	77647	1.14	0.87	3.1	148793.06	17.29	0.0024
	(0.0079)								
Abnormal clinical findings	0.0228**	110.71	78949	1.03	0.87	12.4	148793.06	17.29	0.1879
	(0.0107)								
Infectious	0.0175*	110.71	79217	1.03	0.89	13.7	148793.06	17.29	0.2557
	(0.0093)								
Perinatal	0.0151	100.33	72519	6.02	0.83	0.45	148793.06	17.29	0.5906
	(0.0190)								
Other	0.0141*	110.71	79052	1.01	0.95	23.5	148793.06	17.29	0.2557
	(0.0084)								
Endocrine	0.0137	110.71	79080	1.06	0.88	5.2	148793.06	17.29	0.3735
	(0.0108)								
Obstetric	0.0131	100.33	81692	1.02	0.93	14.4	148793.06	17.29	0.3735
	(0.0105)								
Nervous	0.0120	100.33	81483	1.22	0.83	1.9	148793.06	17.29	0.3735
	(0.0098)								
External causes	0.0114*	110.71	79802	1.01	0.94	26.5	148793.06	17.29	0.2557
	(0.0066)								
Neoplasms	0.0104	100.33	77861	1.55	0.85	0.85	148793.06	17.29	0.5906
	(0.0146)								
Skin	0.0083	100.33	81154	1.13	0.88	3.2	148793.06	17.29	0.5584
	(0.0091)								
Digestive	0.0048	110.71	79437	1.02	0.92	13.4	148793.06	17.29	0.5906
	(0.0069)								
Muskuloskeletal	0.0032	110.71	78507	1.07	0.91	5.03	148793.06	17.29	0.7015
	(0.0072)								
Genitourinary	0.0031	110.71	79351	1.03	0.93	10.6	148793.06	17.29	0.7015
	(0.0065)								
Circulatory	0.0001	110.71	79218	1.06	0.89	5.8	148793.06	17.29	0.9916
	(0.0085)								
Mental and behavioral	-0.0159	110.71	78813	1.12	0.84	2.3	148793.06	17.29	0.2842
	(0.0101)								

Notes: This table presents the point estimates of a control function approach Poisson MLE of municipal emergency room admission rates per 100,000 people in Mexico as a function of instrumented $PM_{2.5}$. We instrument municipal population-weighted $PM_{2.5}$ with the average planetary boundary layer height in the municipality. We present estimates for each ICD-10 chapter. Standard errors are clustered at the municipality level. Significance codes: *** < 0.01,** < 0.05,* < 0.1. We adjust for multiple hypothesis testing by reporting Benjamini-Hochberg (BH) adjusted p.values.

Table C.2: First stage: Effects of the average PBL height on PM2.5

	(1)	(2)	(3)
First stage β from Eq. 2			
Avg. PBLH (meters)	0.0077***	-0.0087***	-0.0044***
	(0.0009)	(0.0009)	(0.0004)
Model Statistics			
Observations	84,034	84,034	84,034
Municipalities	84,034	84,034	84,034
F-test	71.74	101.1	100.3
Average PM25	17.29	17.29	17.29
Average PBLH	579.07	579.07	579.07
Fixed Effects			
Municipality	✓	✓	
Year		✓	
Month		✓	
Municipality × year			✓
Municipality × month-of-the-year			✓
Controls			
Weather controls		✓	✓

Notes: This table presents the point estimates of our first stage on the effects of variations on the height of the PBL on $PM_{2.5}$. We present results for three specifications. The first column only controls for cross-sectional differences between municipalities with municipal fixed effects. The second column adds temporal fixed effects and weather controls which include five indicator variables for the number of days per month between 10 and 30 degrees Celsius in five-degree intervals, indicator variables for the within municipality quintile of daily precipitation, relative humidity and atmospheric pressure. The third column is our prefered specification, which includes municipality by year and municipality by month of the year fixed effects. Standard errors are clustered at the municipality level. Significance codes: $^{***} < 0.01, ^{**} < 0.05, ^{*} < 0.1$.

Table C.3: Marginal effect of $PM_{2.5}$ on emergency room admission rates (Excluding the COVID-19 Period)

	(1)	(2)	(3)
Second stage β from Eq. 3			
$PM_{2.5}$ $(\mu g/m^3)$	0.011***	0.012***	0.027***
	(0.002)	(0.003)	(0.008)
Model Statistics			
Observations	78612	78612	78262
Municipalities	648	648	648
F.Stat (first stage)	75.563	84.645	61.571
Mean admission rate (per 10k)	173.059	173.059	173.059
Avg. municipal population	148.793	148.793	148.793
Fixed Effects			
Municipality	✓	✓	✓
Year		✓	✓
Month		✓	✓
Municipality × month-of-the-year			✓
Municipality × year			✓
Controls			
Weather controls		✓	✓

Notes: This table presents the point estimates of a control function approach Poisson MLE of municipal emergency room admission rates per 100,000 people in Mexico as a function of instrumented $PM_{2.5}$. We instrument municipal population-weighted $PM_{2.5}$ with the average planetary boundary layer height in the municipality. We restrict the sample to all periods before Covid-19 in March 2022. Weather controls include five indicator variables for the number of days per month between 10 and 30 degrees Celsius in five-degree intervals, indicator variables for the within municipality quintile of daily precipitation, relative humidity and atmospheric pressure. Standard errors are clustered at the municipality level. Significance codes: $^{***} < 0.01, ^{**} < 0.05, ^{*} < 0.1$.

Table C.4: Effects of $PM_{2.5}$ on emergency room admission by case outcome

	Home	Hospitalization	Death	Unspecified
Second stage β from Eq. 3				
$PM_{2.5}$ ($\mu g/m^3$)	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	✓	✓	✓	✓

Notes: This table presents the point estimates of a control function approach Poisson MLE of municipal emergency room admission rates per 100,000 people in Mexico as a function of instrumented $PM_{2.5}$. We instrument municipal population-weighted $PM_{2.5}$ with the average planetary boundary layer height in the municipality. Weather controls include five indicator variables for the number of days per month between 10 and 30 degrees Celsius in five-degree intervals, indicator variables for the within municipality quintile of daily precipitation, relative humidity and atmospheric pressure. We present estimates for four reported outcomes: Patient sent home, hospitalization, death, and unspecified. Standard errors are clustered at the municipality level. Significance codes: $^{***} < 0.01, ^{**} < 0.05, ^{*} < 0.1$.