

# PARTICULATE MATTER AMBIENT AIR POLLUTION AND RESPIRATORY DISEASE IN EGYPT

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# ABSTRACT

We assess the effects of air pollutants ( $PM_{10}$ ) on hospital admissions for respiratory diseases in Egypt in 2016. We use a retrospective design and employ a generalized additive model (GAM) to conduct our analysis. Daily hospital admission data for Chronic Obstructive Pulmonary Disease (COPD) and chronic bronchitis were collected from specialized chest hospitals and matched to air pollution data. The results suggest that the concentration of  $PM_{10}$  in the air is an important predictor of respiratory disease. We find that a  $10 \mu\text{g}/\text{m}^3$  increase in  $PM_{10}$  causes a roughly 2% percent higher hospital admission rate for COPD and chronic bronchitis. These additional admissions implicate both increased health expenditure and GDP loss for Egypt.



# CHAPTER ONE

## INTRODUCTION

Air pollution is known to be a risk factor for personal health and an important determinant of various diseases (Pope, et al., 2008; Pope et al., 2014; Ito et al., 2011). Numerous studies exist that examine the effects of an increase in air pollution on the risk of disease and mortality from cardiovascular and cardiopulmonary causes (Pope, Thun, et al., 1995; R. D. Brook et al., 2010). One possible way to quantify air pollution is to measure the concentration of particles with a specific diameter (e.g., particles with diameters between 2.5 and 10 micrometers are referred to as  $PM_{10}$ ). Small-scale particles have proven to be of considerable danger to respiratory health due to their ability to penetrate deep into the lungs and make their way into the blood stream nearly unfiltered. This increases, e.g., the probability of developing cancer (Pope III et al., 2002). Sources for this type of pollution are predominantly pollution from fossil fuel combustion, industrial production, and vehicle traffic (Karagulian et al., 2015).

Various studies have researched the nexus of air pollutant particles with a focus on different parts of the world like North America (Li et al., 2011; Rodopoulou et al., 2014), Europe (Lee et al., 2014; Di Ciaula, 2012), Australia (Hansen et al., 2012) and selected Asian countries like China (Cai et al., 2014), Taiwan (Chan et al., 2006) and India (Nagpure et al., 2014). The results unanimously point to the same direction: Air pollution is, regardless of the particular measurement, a very important predictor of various health outcomes, measured for instance in terms of hospital admission counts or number of deaths.

One of the world regions with areas that suffer from particularly high premature mortality rates due to air pollution is the Middle East (Lelieveld et al., 2015). In the Middle East, 125,000 deaths occurred due to outdoor and household air pollution in 2013 according to the Global Burden of Disease (GBD) study (see A. H. Mokdad et al., 2016 for an overview). Despite that observation, research on the pollution-health nexus that focuses on countries in this region is extremely sparse. In fact, the only paper existing was published relatively recently and studies Saudi Arabia (Nayebare et al., 2017). It is therefore crucial to expand the knowledge on the relationship between health and air pollution to other countries in the Middle East. A particularly interesting case is Egypt. For example, the greater area surrounding Egypt's capital, Cairo, is the most polluted metropolitan area that is not located in Asia and therefore one of the most polluted regions in the world. It comes as no surprise that lower respiratory infections, COPD, and lung cancer cause around 10% of all premature deaths in Egypt. In addition, air pollution is featured in the five most dangerous risk

factors of disease and premature death in Egypt (Wang et al., 2012). Hence, the relationship between air pollutant concentrations and respiratory diseases is an important topic, not only for researchers, but also from a policy perspective, especially for decisions affecting the health care system and environmental legislation.

Therefore, our research focuses on the important relationship between air pollution (in particular  $PM_{10}$ ) and respiratory diseases in Egypt. We employ patient-level data from chest hospitals in Egypt and combine them with air pollution and weather data. The statistical method of choice is the generalized additive model (GAM), taking the form of a Poisson regression.

The results suggest that air pollution is a risk factor for respiratory disease in our sample. Higher concentrations of  $PM_{10}$  are connected to higher admission counts for COPD. Exposure to high levels of pollution also increases the risk of suffering a disease episode when you have chronic bronchitis.

To our knowledge, this is the first epidemiological study on the air pollution—health—nexus in Egypt and the first study to examine the health effect of specifically  $PM_{10}$  levels in the Arab world. In addition, studying Egypt allows us to study an environment with a very high average level of air pollution.<sup>1</sup>

The remainder of this report is structured as follows: The next section gives an overview of our study design and statistical framework. Chapter 3 introduces the data employed in the analysis. Chapter 4 discusses the results, and Chapter 5 covers the conclusions, caveats, and next steps.

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<sup>1</sup>The average concentration of  $PM_{10}$  in our dataset is around 7× higher than in Hansen et al. (2012) studying Adelaide/Australia, about 4× higher than in Braga et al. (2001) studying ten U.S. cities, and still around 100% higher than the pollution levels studied in Shakerkhatibi et al. (2015) and Cai et al. (2014) studying Tabriz/Iran and Shanghai/China, respectively.

## CHAPTER 2

# EMPIRICAL APPROACH

Our dataset contains only patients who *have* experienced some event of interest. In our case, all patients were admitted to a hospital due to respiratory diseases. Hence, the study design is focused on the time, when a specific event occurred. Here, we are interested in the date of admission to one of the studied hospitals. Using patient-level data, we can employ daily admission counts for specific diseases, which can be used to assess the relative risk of admission due to air pollution shocks.

Our statistical framework is closely related to the model used in Braga et al. (2001). Since we deal with admission *count* data, we choose a commonly used approach and fit a generalized additive Poisson regression model for each diagnosis separately. To account for possible effects of air pollution that do not occur on the same day but in the days following high pollutant concentrations, we specify a distributed lag model. Hence, the full model takes the form:

$$\log(E(Y)) = \alpha + \beta_1 PM_{10,t} + \dots + \beta_q PM_{10,t-q} + \delta X_t + \varepsilon_t \quad (1)$$

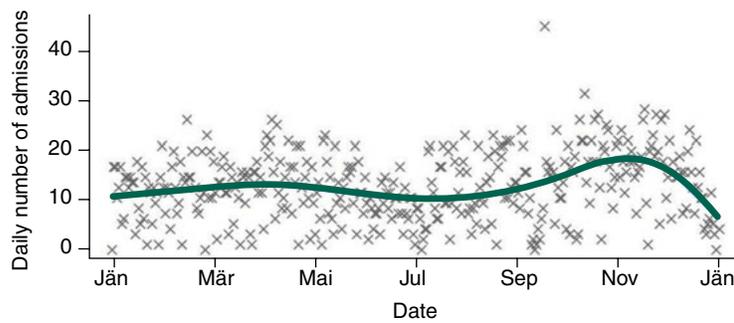
where  $Y$  denotes the daily admission count of a particular respiratory disease,  $PM_{10,t}$  denotes the concentration of particulate pollutants and  $X_t$  is a matrix of control variables.  $\varepsilon_t$  denotes the error term. We follow Braga et al. (2001) and use  $q = 5$  lags to capture possible delayed effects. Note that  $\beta_1$  to  $\beta_q$  can be interpreted as the percentage effects of a unit increase of the concentration of  $PM_{10}$  in period  $q$  on the relative risk of hospital admission due to a respiratory disease on day  $t$ . Please note that the use of just the present day's pollutant concentration as dependent variable is a constrained lag model with  $\beta_2 = \beta_3 = \dots = \beta_q = 0$ . This assumption can often be seen to be restrictive and possibly introduces bias to the analysis; see Braga et al. (2001).

We use a set of control variables that is standard and commonly found in related works. Our control matrix  $X_t$  contains smooth spline functions to capture time trends and meteorological effects on hospital admissions. Smooth functions of relative humidity, temperature, one day lagged temperature, and barometric pressure are employed to capture possibly non-linear weather effects. In particular, we use B-splines of degree 3 with 6 degrees of freedom.<sup>2</sup> As an example, the smooth function of time used to capture non-linear time effects in the overall

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<sup>2</sup>This translates to a commonly employed rule of thumb to use  $(\text{number of years} \times 7) - 1$  knots when creating a cubic spline. This is viewed as a more or less ideal trade-off between the number of parameters to estimate and level of smoothness when approximating the data.

**FIGURE 1:** SMOOTH FUNCTION OF TIME FITTED HOSPITAL ADMISSION COUNTS



sample is provided in Figure 1. In addition, we use weekday dummies to capture, e.g., possible effects of weekends. Finally, we add monthly dummies to be able to capture effects, such as the infamous "black cloud" (the traditional burning of agricultural waste in autumn, see, e.g., Marey et al., 2010) or Ramadan, which took place from the beginning of June to the beginning of July in 2016.

For more details regarding empirical approach please refer to Braga et al. (2001).

# CHAPTER 3

## DATA

We combine data from three different sources: Patient-level hospital admission data as the dependent variable, daily air pollution levels (particulate matter) as main explanatory variables, and meteorological variables to control for weather effects. All three data sources and transformations are discussed below. Summary statistics are provided in Table 1. A map of the hospitals and air pollution stations can be found in Figure 2. The air pollution measuring station we use is tagged “Mahla kobra.”

We use hospital data that have been collected and provided by two specialized chest hospitals in Northern Egypt. The first dataset with 3,704 observations (76.5%) comes from the 450,000 people city of Al Mahalla Al Kubra, the second dataset with 1,134 observations (23.5%) from Schibin al Kaum, a city of roughly the same size in the governorate of Al-Minufiyya. Al Mahalla Al Kubra is a large industrial city in the Nile Delta; it contains the largest textile industry complex in the Middle East, established during the 1950s. The city also hosts many other industries within the value chain of textile industries. Schibin al Kaum is the capital city of Menofia Governorate, about 50–60 km north of Cairo.

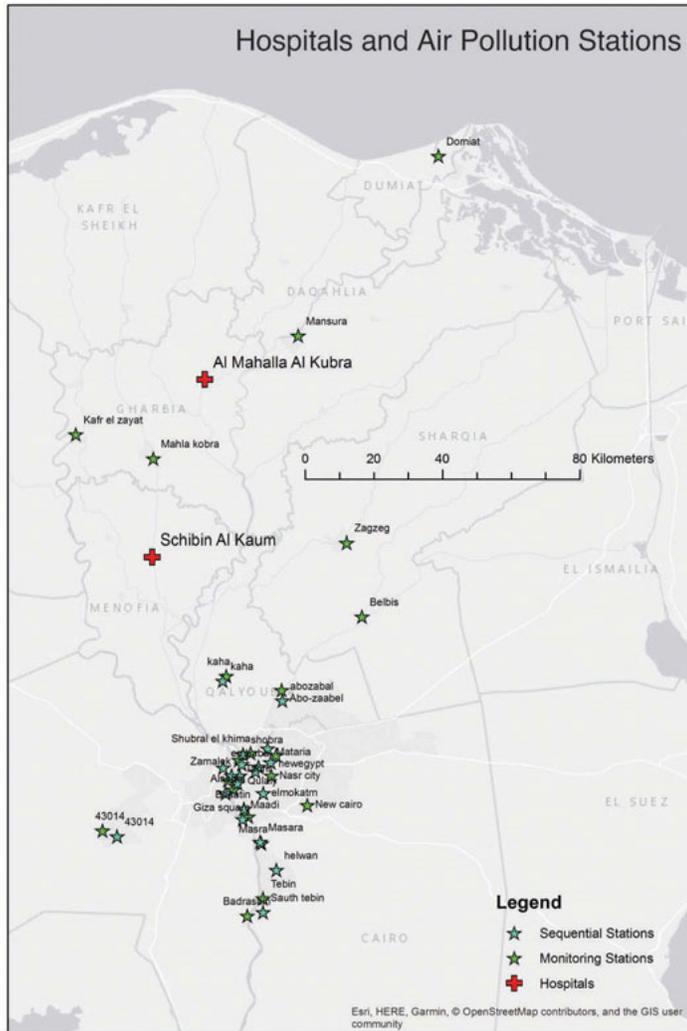
All 4,838 observations (admitted and diagnosed patients) are from the year 2016. The dataset consists of 37.5% females and 62.5% males. The average age is 47.5 years, median age is 55 years, and the dataset covers patients from 1 month to 97 years of age. We can also give a rough description of occupations, as the dataset from Al Mahalla Al Kubra provides occupation categories for around 30% of the sample. This 30% consists of 50% retirees and 25% children, whereas the rest is a mixture of mostly farmers, drivers, employees, engineers, and workers. Hence, we conclude that the analysis is especially relevant in assessing

**TABLE 1: SUMMARY STATISTICS**

Statistic	N	Mean	St. Dev	Min	Max
PM <sub>10</sub>	298	153.252	56.644	41.417	418.083
Chronic Bronchitis	342	5.006	2.750	1	15
COPD	350	4.731	2.492	1	16
Temperature	366	74.995	11.109	48	100
Pressure	366	29.966	0.150	29.690	30.420
Reactive Humidity	366	52.746	12.029	16	80

Note that 2016 was a leap year and therefore had 366 days.

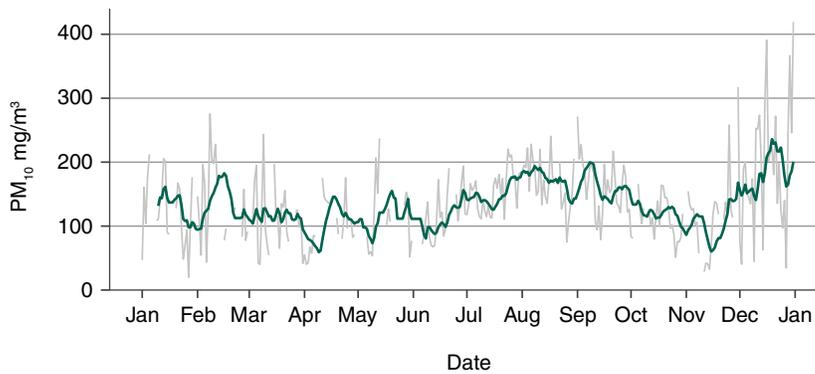
**FIGURE 2:** MAP OF HOSPITALS AND AIR POLLUTION STATIONS



risk of disease for a population with relatively low socioeconomic status. We aggregate the patient-level data to daily admission counts for 2016. In the process, we split the sample into different diagnosis categories. As the dataset is comparatively small, we restrict the analysis to diagnosis categories that cover at least 80% of the days in 2016. This leaves us with the two different diagnosis categories: chronic bronchitis (35.4%) and COPD (34.3%). Note that we still effectively cover around 70% of the available sample. Further analysis will become possible once new data collection strategies following standard classification systems like the ICD-10 norm have been implemented.

Air pollution data are collected using the closest online monitoring station to both hospitals, located at N30°46'31.0686" E31°0'58.3482". This station is installed for the specific purpose of capturing industrial pollution. However, in this study, we do not focus on specific pollution sources like fossil fuel combustion, industrial production, or vehicle traffic (Karagulian et al., 2015). We are agnostic as to where the variation in air pollution that we observe comes from. The data have been provided by the Egyptian Environmental Affairs Agency (EEAA). The air pollution station provides daily PM<sub>10</sub> levels readings, which are then harmonized by

**FIGURE 3:** PM<sub>10</sub> TIME SERIES (GREY) AND TEN-DAY TRAILING MOVING AVERAGE (GREEN)



EEAA. EEAA reports daily averages based on these readings and reported records for 80% of days in 2016, effectively covering 298 days. Figure 3 provides the raw time series as well as a ten-day moving average of the data.

As with every empirical study assessing the health effects of air pollution on health, attribution of the admitted patient to the representative air quality is key. Following established practice in literature, the closest distance approach between the locations of weather and air pollution stations and the hospitals is chosen. Three arguments in favor of using the described dataset with the closest proximity attribution are offered. First and most strikingly, there is no other available data that is collected closer to the studied hospitals on which one could rely. Second, we use data from specialized hospitals. Therefore, the commuting area might well be larger than what would be expected from a standard general admissions hospital. The attribution of the air pollution monitoring station to the hospitals is already based on spatial proximity. Both hospitals and air pollution stations are under the same airshed, therefore it might well be that the registered meso-variation in air pollution is representative of particle exposure in the catchment area of the hospitals. Thirdly, we have no reason to expect drastic differences in weather between Cairo and the studied cities due to geographical proximity, the lack of mountains between them, and the general climatic patterns in Egypt: weather in Egypt is largely homogenous, i.e., extremely dry and hot. Therefore, the expected climatic effects on air pollution measurements can be assumed to be largely homogenous. Hence, the argument presented is that all three datasets will on average be a good approximation of the actual (but unfortunately unavailable) concentration measurements in the studied areas.

The weather data are collected by a weather station located at the airport in Cairo. The station logs daily averages of temperature, relative humidity, and barometric pressure, as well as other meteorological variables. The data are collected via the Application Programming Interface (API) of *WeatherUnderground*, a commercial weather service that compiles data both from official government sources as well as from private weather stations.

To test for stationarity in our time series, we run Augmented Dickey Fuller tests (see Fuller, 1976) for the PM<sub>10</sub> time series, as well as for the hospital admission time series. The null hypothesis of a unit root can be rejected for all time series except chronic bronchitis admissions with a p-value of  $< 0.01$ . After controlling for a smooth time trend (which we include in every regression by default), the possible non-stationarity issue disappears for the chronic bronchitis time series as well.

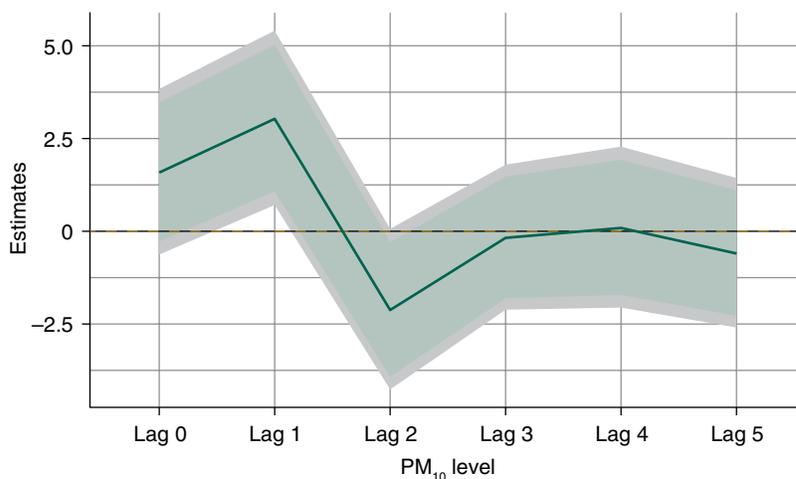
# CHAPTER 4

## RESULTS

We find that air pollution is an important predictor of hospital admissions in Egypt. We find significant effects for COPD and chronic bronchitis. We present figures that display the estimated effects of a  $10 \mu\text{g}/\text{m}^3$  increase in  $\text{PM}_{10}$  levels on the admission counts of the studied diseases and how they play out over time (Figures 4 and 5). The effects are displayed by time since the air pollution shock, where lag 0 denotes the concurrent effects, and lag 1 refers to effects on hospital admissions the day after, lag 2, 2 days after and so on. The shaded areas depict confidence intervals (at the 95 percent level for the light grey area and at 90 percent for the green area). The numerical results may be found in Table A.1 in the appendix. We transform the estimates to correspond to a % increase for easier interpretation. There does not seem to be any significant effect of air pollution on respiratory disease admissions on the same day; however, the lagged effects on admission rates do seem to play a role up to a timeframe of two days for our COPD and chronic bronchitis admissions.

For COPD, the day after high pollutant counts we observe a significant increase in hospital admissions (+3%), as seen in Figure 4. On the next day, however, we would expect a significant *decrease* of hospital admissions (using a confidence interval of 90%). This is usually referred to as “harvesting” in epidemiological literature (Bhaskaran et al., 2013). It refers to the premature, short-term displacement of highly vulnerable patients due to high probability of admission on high pollution days. In other words, patients that were supposed to go to

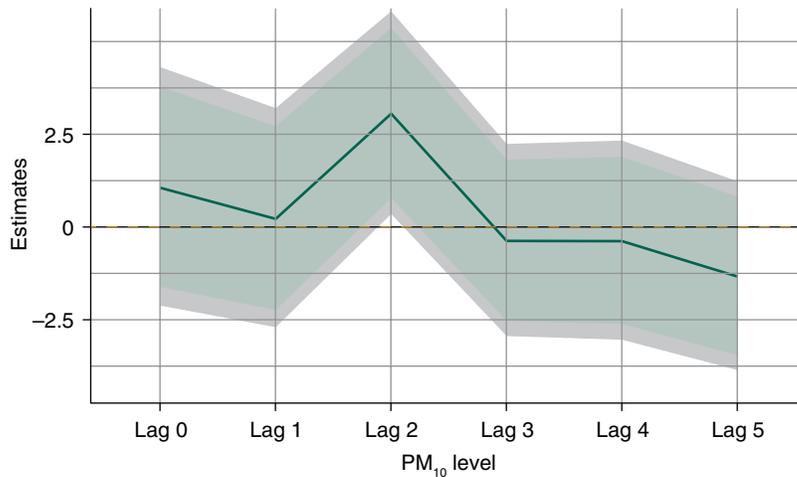
**FIGURE 4:** COPD: DISTRIBUTED LAG MODEL COEFFICIENT ESTIMATES WITH 95% AND 90% CONFIDENCE INTERVALS



the hospital on Wednesday for their COPD disease, were already “harvested” by the unexpected high pollution shock on Monday and Tuesday, meaning that they went to the hospital earlier than they would have. This effect is one of the reasons why employing distributed lag models proves to be especially useful in epidemiology, as those short-term effects may display opposite signs indicating countervailing effects, which tend to get lost when only examining cumulative effects.

For chronic bronchitis, we find increases in hospital admissions of around 2.4% the second day after high pollution (see Figure 5). Note that this implies that it is not necessary for an air pollution shock to demonstrate its health effects on the very same day. This may seem puzzling at first; however this is common in the literature (see, e.g., Braga et al., 2001). Possible explanations are varying incubation times of respiratory disease episodes or varying amounts of time that individuals take to act on their discomfort level from their medical condition and decide to visit a hospital.

**FIGURE 5: CHRONIC BRONCHITIS: DISTRIBUTED LAG MODEL COEFFICIENT ESTIMATES WITH 95% AND 90% CONFIDENCE INTERVALS**



An unbiased estimate of the cumulative effects can be obtained by summing over all lag coefficients (see, e.g., Hamilton, 1994). Using this approach, the cumulative effect of a  $10 \mu\text{g}/\text{m}^3$  shock on COPD patient admissions is +1.8%, and the effect on chronic bronchitis hospital admission is +2.14%.

These effects are comparable to similar studies with respect to sign and magnitude. Braga et al. (2001) report a +1.7% effect on COPD admissions after  $\text{PM}_{10}$  shocks. Cai et al. (2014) find a +1.77% effect on asthma hospital admissions in Shanghai after days with high  $\text{PM}_{10}$  concentrations. However, more diverse effects are common in the literature that deals with different diseases and regions. For instance, Rodopoulou et al. (2014) find a +3.1% effect on cardiovascular disease admissions due to  $\text{PM}_{10}$  particles and Hansen et al. (2012) find a +0.88% effect on respiratory disease hospital admissions after air pollution shocks in Australia.

## CHAPTER 5

# CONCLUSION, CAVEATS, AND NEXT STEPS

In this manuscript, we estimate the effect of particulate air pollution on respiratory health in Egypt. We employ data from air pollution stations and weather stations, and patient data from two specialized chest hospitals in our analysis. Our results suggest that the concentration of  $PM_{10}$  in the environment is indeed a predictor of respiratory diseases such as Chronic Obstructive Pulmonary Disease (COPD) and chronic bronchitis. We argue that high pollution environments can be a trigger of disease episodes. Quantitatively, we are aligned with previous studies regarding the sign and size of the effects. The main contribution of our analysis is the novelty of the geographical area under examination (as the relationship of pollution and health remains largely unexplored in the Middle East and especially in Egypt) and the setting of the study in an environment with extremely high average pollution values.

We would like to stress that we analyze only respiratory diseases, and thus do not take into account other health issues that have a high probability of being influenced by air pollution. In addition, no mortality effects and education effects that might well introduce substantial additional costs are considered in this study. Unlike in the Cost of Environmental Degradation study (2018), which the World Bank also carried out jointly with EEAA, where the focus was on estimating the holistic effect of air pollution on mortality and morbidity, with established exposure-response functions from the international literature, this study is the first to statistically estimate the epidemiological effects, with Egyptian data, in order to establish Egyptian pollution-health relationships.

When interpreting the results, one has to keep in mind that the effects on hospital admissions are net of so-called defensive expenditures. High pollution days do not only lead to higher hospital admission rates, but also to other behavioral responses of individuals. For instance, people might avoid outdoor exposure or use countermeasures that are readily available, like inhalers or face masks (see Zhang and Mu, 2017). This results in a downward bias of the estimated biological response. In other terms, using hospital admission rates as a behavioral dependent variable merely accounts for a part of the overall biological effect. Thus, our analysis is likely to produce conservative estimates. Furthermore, since we capture only public hospitals in our analysis, we think that our estimates are larger than those of private hospitals would be, due to the fact that patients who are able to afford private health care are also more likely to afford defensive investments such as air purifiers, and are less likely to work outdoors (where they would be more exposed).

Another issue that possibly introduces a bias to our analysis is the fact that some groups (e.g., more wealthy or mobile) persons might migrate out of the polluted regions—leaving a biased sample because of spatial sorting. However, we argue that the time horizon where migration happens is at least medium term. Thus, our analysis of the effects of air pollution based on short-term variation should not suffer a substantial bias in this regard.

Environmental concentrations (for which we have data), are one step removed from exposure (which also importantly incorporates behavioral responses among other things). On the exposure side, it has generally been found that socioeconomic differences in air pollution exposure can be explained by better-off persons sorting into less polluted areas (see for instance Depro et al., 2015). In addition, better-off persons usually tend to work in white collar jobs as opposed to blue collar jobs, which results in them being spatially further removed from the point source pollution (e.g., working in an air conditioned and air purified office, versus on a construction site), and also in them breathing in less intensely (compare for example the heavy manual labor of a construction or agricultural work, with office-based work). Our sample is drawn from public hospitals, and our descriptive assessments of socioeconomic data available (not shown in this report), indicate that the sample we analyze is from a lower socioeconomic strata, and may therefore not be regarded as being representative for the population of Cairo as a whole.

The analysis and results presented in this report pertain to two hospitals, as these two hospitals had readily available electronic data recordings of patient admissions and other information such as diagnoses. The team has started to also collect data from other public hospitals, in order to get a more representative hospital sample. Data collection and analysis for these other hospitals are expected to take some time, as paper-based records need to be converted to electronic data entries, and data quality assurance procedures will have to be employed. Once the data from these additional hospitals becomes available, it will be integrated into the analysis.

Areas for future research include the effect of the various components of  $PM_{10}$ —depending on their sources—on disease and mortality. Another possible path is a detailed analysis of subgroups in the population. As is commonly found, younger (in particular infants) and older (in particular retirees) individuals suffer disproportionately from air pollution (see Buka et al., 2006 and Simoni et al., 2015). Due to data restrictions, this issue has not been explored in this study. In addition, an interesting topic for further research is to look deeper into the health effects of long-term exposure to air pollution to complement the short-term analysis of this report. (This report looks at day-to-day variations in air pollution concentrations.)

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# APPENDIX

## ESTIMATION RESULTS

**TABLE A1:** DISTRIBUTED LAG MODEL RESULTS

	Lag 0			Lag 1			Lag 2			Lag 3			Lag 4			Lag 5		
	Est.	CI-	CI+	Est.	CI-	CI+	Est.	CI-	CI+	Est.	CI-	CI+	Est.	CI-	CI+	Est.	CI-	CI+
Chronic bronchitis	0.88	-1.56	3.38	0.24	-2.00	2.53	<b>2.42</b>	<b>0.34</b>	<b>4.53</b>	-0.22	-2.19	1.79	-0.22	-2.26	1.86	-0.96	-2.89	1.02
COPD	1.58	-0.63	3.84	<b>3.03</b>	<b>0.71</b>	<b>5.41</b>	-2.12	-4.26	0.06	-0.18	-2.11	1.80	0.09	-2.06	2.28	-0.60	-2.59	1.44

Estimates correspond to a % increase in admissions due to a 10 µg/m<sup>3</sup> increase in PM<sub>10</sub> levels. Lower and upper bounds correspond to 95% confidence intervals.



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