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Particulate Matter Concentrations, Sandstorms and Respiratory Hospital Admissions in Israel

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ABSTRACT: **Background:** Exposure to air pollution in the form of particulate matter smaller than 10 μm in diameter (PM10) has been associated with increased morbidity and mortality. However, since air pollution is correlated with confounding factors that might otherwise affect health, identifying the causal link has proven challenging.

Objectives: To identify the effect of PM10 on hospital admissions due to respiratory illnesses.

Methods: We used the Instrumental Variable (IV) methodology to control for confounding factors affecting hospital admissions. Exploiting the timing of sandstorms as an instrumental variable allows for a better estimate of the relationship between PM10 and hospital admissions. Data on PM10 concentrations and hospital admissions were compiled for Israel's two largest cities, Jerusalem and Tel Aviv, for 2007–2009. We compared our IV estimates to those derived from a Poisson regression, which is commonly used in the literature.

Results: Sandstorms led to an increase of 307 μg/m^3 of PM10 concentrations. A 10 μg/m^3 increase in PM10 is associated with a 0.8% increase in hospital admissions due to respiratory conditions, using IV methodology. The same finding was noted using the Poisson regression.

Conclusions: The association between PM10 and hospital admission reflects a primarily causal relationship. Instrumental variable methodology could be applied to analyze the effect of air pollution on hospital admissions.

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KEY WORDS: PM10, sandstorms, air pollution, hospital admissions, instrumental variable (IV)

A rich literature has demonstrated that exposure to atmospheric particulate matter (PM), which arises from both natural and industrial activity, is associated with increased hospital admissions for respiratory health problems [1-4]. However, the degree to which this represents a causal link is still an open question. Confounding factors that may be partly responsible for the observed association include, among others, pollens, autocorrelations, seasonality, and preexisting diseases such as cardiorespiratory diseases and viral diseases [5-8]. This paper will attempt to address the issue of confounding factors directly by using the Instrumental Variable approach (IV). Understanding the causal link between particulate matter and hospital admissions is crucial for setting a rational public health policy that properly weighs the benefits and costs of stricter standards on particulate matter emissions.

The use of IV is very common in the social sciences [9] but its adoption by epidemiologists is quite recent and limited [10-13]. With the IV approach, a variable is identified which is correlated with particulate matter concentrations (PM10, i.e., particulate matter > 10 μm in diameter) but does not directly affect health outcomes. The IV approach, when its assumptions are satisfied, can generate causal estimates of the dose-response relationship between PM10 and hospital admissions due to respiratory conditions. The timing of sandstorms is highly random and should otherwise not be related to factors affecting health outcomes, making sandstorms a natural candidate for IV.

This paper exploits the timing of sandstorms in Israel, an important source of ambient air pollution in many countries in the Middle East region and worldwide [14]. Sandstorms dramatically increase ambient PM10 concentrations, which may lead to an increase in respiratory and other illnesses. PM10 is associated with inflammatory processes in the upper tracts of the lungs, and depending on the exact size of the particulate matter it is deposited in the bronchi, bronchioles and even the alveoli [15]. Sandstorms mainly consist of coarse particles (2.5–10 μm diameter), which are mostly silica particles (sand) and very little industrial contaminants [15]. Several studies have documented increased hospital admissions during sandstorms in Asia [7,15-20] and Australia [21]. One study dealt with the effect of PM10 on emergency room (ER) admissions for cardiopulmonary illnesses [8]. Other studies documented increases in mortality following sandstorms in Australia and the Mediterranean region [22,23]. Asian and Australian sandstorms are similar to Mediterranean sandstorms, though they affect different populations. These studies show that sandstorms lead to an increase in hospital admissions due to chronic obstructive pulmonary disease (COPD), asthma, pneumonia, ischemic heart disease and cerebrovascular disease. However, many of these studies report results that are not statistically significant and others do not control for potential confounding factors [7].

DATA AND METHODS

This study uses data on air pollution and hospital admissions for the two largest cities in Israel, Jerusalem and Tel Aviv, for the period 2007–2009. Both cities have heavy traffic. The air pollution data were obtained from the Israeli Ministry of Environmental Protection, which collects hourly readings of air pollutants from monitors throughout Israel. During the sample period there were four monitors in Jerusalem and two in Tel Aviv. Monitors are similarly distributed in the two cities and are subject to the same rules and regulations. The hourly readings were aggregated to daily averages. The Ministry of Environmental Protection also reports the date and time of sandstorms, temperature, and relative humidity and precipitation for each day during the period of analysis. Summary statistics for these key variables are presented in Table 1. The sample mean of PM10 (55.575 $\mu g/m^3$) is higher than the annual standard recommended by the World Health Organization which is 20 $\mu g/m^3$.

The hospital admissions data were collected by Israel's Ministry of Health. These data record each hospital admission due to respiratory issues in Israel's two largest cities (Jerusalem and Tel Aviv) from 1 January 2007 to 31 December 2009. The respiratory conditions include COPD, asthma, and respiratory abnormalities. Respiratory abnormalities are a broad classification of respiratory illnesses used by hospitals to classify patients and include most respiratory conditions not related to asthma and COPD. The study does not include data on cardiorespiratory illnesses, since the effect of sandstorms on these illnesses is already documented [8]. Data on sandstorms were collected from media items and official warnings published by the Israeli Ministry of Environmental Protection.

In order to account for the confounding factors which are the result of weather and human behavior, several control variables are also included in the analysis. Dummy variables are used to account for differences between weekdays and weekends. Since religious Israeli Jews observe the Sabbath, spanning from Friday evening to Saturday evening, hospital admissions are often lower on Friday nights and Saturdays, as people prefer postponing their visit to the ER if their condition is not too severe. Importantly, the analysis also includes city fixed effects, which will absorb time-invariant differences in pollution levels and hospital admission across cities. A fixed effect for season (fall, winter, spring, summer) and a time trend are also included in the analysis. These control for long-term trends in the data. Since our dataset is at the aggregate level, we do not have data on individual level confounding factors such as age and preexisting health condition.

This study uses the IV methodology (see [24] for a detailed description of the methodology) and compares the results to the Poisson regression approach commonly used in the literature. The first stage of the IV methodology estimates the relationship between daily PM10 concentrations and the occurrence of a sandstorm (our instrument), and a set of control variables. Equation 1 specifies the first stage equation:

(1) $PM10_{it} = \beta Sand_{it} + \gamma X_{it} + \varepsilon_{it}$

where $PM10_{it}$ is average daily concentrations of particulate matter smaller than 10 μm at city i on day t. $Sand_{it}$ is a dummy variable taking the value of 1 if there was a sandstorm at city i on day t. X_{it} is a vector of the set of standard control variables: average daily temperature, relative humidity, precipitation, a dummy variable for each season, a dummy variable for each city, a dummy variable for weekends, and a time trend. β, γ are the regression coefficients where β measures the effect of sandstorms on PM10 concentrations. Finally, εit is the residual term, capturing all other factors not included in the model.

The first stage is estimating the predicted value of PM10 based on the timing of sandstorms and other explanatory variables. This predicted value will be used in the second stage to estimate the effect of PM10 on hospital admissions. Since the instrument (timing of sandstorms) is thought to be exogenous, the predicted values of PM10 that are estimated in the first stage should be uncorrelated with any confounding factors. Equation 2 specifies the second stage equation:

(2) $Admissions_{it} = \lambda pPM10_{it} + \eta X_{it} + \omega_{it}$

where $Admissions_{it}$ is the number of hospital admissions due to respiratory conditions (COPD, asthma, and respiratory abnormalities), at city i on day t. $pPM10_{it}$ is the predicted value of PM10 from the first stage. X_{it} is a vector of the set of standard control variables described above. λ and η are the regression coefficients. Finally, ω_{it} is the residual term, capturing all other confounding factors. The parameter of interest is λ, which gives us the effect of PM10 concentrations (in 10 $\mu g/m^3$) on hospital admissions.

RESULTS

Table 1 provides statistics for the main variables used in the analysis. The mean hospital admissions rate for lung-related diseases is 3.87: respiratory admissions being roughly half of the lung-related admissions, the other half being COPD and asthma admissions. The variability in lung-related hospital admissions is quite striking, and there is also substantial variability in daily mean PM10 concentrations, ranging from 6.5 to 1014.6 $\mu g/m^3$.

Table 2 presents the effect of sandstorms on PM10 concentrations (the first stage of the IV methodology). Each column presents the results of a different regression. Both regressions are based on equation 1. Column 1 presents a simpler model with fewer control variables, while column 2

Table 1. Summary statistics of the main variable

Variable	Mean	SD	Min	Max
Lung-related diseases admissions	3.870	2.667	0	19
Daily COPD admissions	1.049	1.085	0	9
Daily asthma admissions	0.860	0.981	0	6
Daily respiratory admissions	1.961	1.915	0	12
Daily mean PM10 concentrations (μg/m3)	55.575	64.107	6.5	1014.6
Daily mean precipitation (mm)	0.046	0.228	0	3.308
Daily mean relative humidity	61.334	16.067	2.7	100
Daily mean temperature (C°)	19.954	5.941	0.9	31.7

SD = standard deviation, COPD = chronic obstructive pulmonary disease

Table 2. Relation between sandstorms and PM10 concentrations

	1	2
Sandstorms	306.84 (12.67)***	298.70 (11.81)***
Temperature	–	1.73 (0.40)***
Humidity	–	-0.46 (0.09)***
Precipitation	–	3.10 (5.62)
Weekends	–	-3.91 (2.59)
N	2180	2011
R^2	0.24	0.30
F test	113.23	87.88

The dependent variable is PM10 concentrations in μg/m3. All regressions include city and season fixed effects and a time trend.

Asterisks denote the level of statistical significance: *$P < 0.1$, **$P < 0.05$, ***$P < 0.01$

adds several control variables to the specification presented in column 1. Each cell presents the regression coefficient for a different variable, with the standard error in parenthesis. A sandstorm is associated with an increase of 306.84 μg/m³ in PM10 concentration (column 1). This is a steep rise from the daily mean of 55 μg/m³. This association is highly significant, with an *F*-test equal to 113, and only changes slightly when we control for additional control variables (column 2). The results in Table 2 suggest that sandstorms are not a weak IV. Additional results presented in the online Appendix suggest that the IV does not violate the exclusion restriction, i.e., it is probably uncorrelated with other confounding factors.

Table 3 provides the results of the effect of PM10 on respiratory conditions. Similar to Table 2, each column presents the results of a different regression model, and every cell presents the regression coefficient and the standard error of a different variable. PM10 concentrations are reported in units of 10 μg/m³ in order to facilitate a comparison with the literature. First, column 1 presents the Poisson regression as a baseline. The coefficient of PM10 equals 0.008, i.e., an increase of 10 μg/m³ of PM10 will result in an additional risk of 0.8%. The control variables are also highly statistically significant. Temperature is negatively associated with hospital arrivals, as is humidity. Precipitation is negatively correlated with hospital arrivals and has a very marked effect. Finally, weekends are strongly negatively correlated with hospital arrivals due to the Sabbath.

Table 3. Effect of PM10 on hospital admissions

	1	2	3	4	5
	Poisson	**OLS-FE**	**IV**	**IV-Poisson**	**IV-logs**
PM10	0.008 (0.002)***	0.04 (0.01)***	0.04 (0.02)**	0.01 (0.005)**	0.01 (0.004)**
Temperature	-0.2 (0.04)***	-0.8 (0.2)***	-0.8 (0.2)***	-0.2 (0.04)***	-0.2 (0.04)***
Humidity	-0.01 (0.01)	-0.06 (0.04)	-0.06 (0.04)	-0.01 (0.01)	-0.01 (0.01)
Precipitation	-1.2 (0.6)**	-4.0 (2.4)*	-4.0 (2.4)*	-0.8 (0.7)	-0.9 (0.6)
Weekends	-1.8 (0.3)***	-6.6 (1.1)***	-6.6 (1.1)***	-1.8 (0. 3)***	-1.8 (0.3)***
N	2011	2011	2011	2011	1909
R^2	0.12	0.32	0.78		0.83
F test for excluded instruments	–	–	639.22	–	612.64

The dependent variable in columns 1–4 is the number of hospital arrivals due to lung illnesses (the sum of COPD, asthma, and respiratory abnormalities). Dependent variable in column 5 is log of hospital admissions. City and season fixed effects, as well as a time trend, are included in all columns. Column 1 presents the Poisson regression. Column 2 presents an ordinary least squares (OLS) regression. Column 3 presents the Instrumental Variable regression. Column 4 presents a Poisson regression which is estimated using an instrumental variable. Column 5 presents an IV regression where the dependent variable is log admissions.

Asterisks denote the level of statistical significance: *$P < 0.1$, **$P < 0.05$, ***$P < 0.01$

Column 2 provides the results of the model where city fixed effects are included and the results are derived only from variation within city over time. The coefficient of PM10 equals 0.04, i.e., an increase of 10 μg/m³ of PM10 will result in an additional 0.04 admission*. Translating this coefficient into percentages suggests that a 10 μg/m³ increase in PM10 concentrations will lead to an increase of 1% in hospital arrivals.

Column 3 reports the results using the IV methodology. The *F*-test statistic for the excluded instruments is large (F = 639.22) relative to the common threshold of 10, suggesting that the instrument has a very strong relationship with daily pollution variation. The coefficient in column 3 is identical to the one in column 2, suggesting that a 10 μg/m³ increase in PM10

*We use the level of admissions as the dependent variable whereas the literature usually uses the 1n of admissions. Since admissions are sometimes zero the 1n transformation is inappropriate in our case. To verify that this difference is not affecting the results, column 5 in Table 2 presents a regression where 1n admissions is the dependent variable

Table 4. Effect of PM10 on COPD, asthma, respiratory abnormalities, and abdominal pain

	COPD	Asthma	Respiratory abnormalities	Abdominal pain
Panel A. Poisson				
L=0	0.01 (0.003)***	0.008 (0.003)***	0.006 (0.002)***	0.002 (0.0014)
L=1	0.004 (0.003)	0.01 (0.003)***	0.003 (0.002)	0.002 (0.0014)
L=2	-0.001 (0.003)	0.002 (0.004)	0.002 (0.002)	0.001 (0.001)
L=3	0.0001 (0.003)	-0.005 (0.004)	-0.003 (0.003)	0.001 (0.001)
Panel B. IV				
L=0	0.02 (0.008)***	0.007 (0.007)	0.01 (0.01)	0.02 (0.02)
L=1	-0.005 (0.008)	0.008 (0.007)	-0.006 (0.01)	0.003 (0.02)
L=2	-0.002 (0.008)	0.02 (0.007)**	-0.007 (0.01)	-0.02 (0.02)
L=3	-0.02 (0.008)	-0.009 (0.007)	-0.005 (0.01)	-0.005 (0.02)

L = x symbols the number of lags for PM10, where x takes the values 0, 1, 2 and 3.

All regression included the same set of controls: relative humidity, temperature, rain, and weekend, season, and city dummies.

Asterisks denote the level of statistical significance: *$P < 0.1$, **$P < 0.05$, ***$P < 0.01$

leads to an increase of 1% in the number of hospital arrivals. These results are in line with results reported by Atkinson et al. [3] and Chen et al. [13], suggesting that the percentage increase equals 0.9% and 1.6%, respectively. Since our results are well within their 95% confidence intervals (0.6%–1.3% and 0.25%–2.99%, respectively), the differences between the studies are not statistically significant.

Column 4 of Table 3 reports the results of an estimator suggested by Nichols [25], which allows for an IV estimation using a Poisson regression. The effect of PM10 is very close to the standard Poisson estimator, and the coefficient only changes slightly from 0.008 to 0.01. Finally, to enable a closer comparison with the literature, column 5 of Table 3 provides results using the IV estimator with a different outcome variable, the 1n of hospital admissions rather than the number of admissions. The results are largely unchanged but slightly stronger, and the effect of a 10 μg/m^3 increase in PM10 concentrations on hospital admissions is now 1%.

Table 4 presents a more in-depth analysis of the IV approach, focusing on three different respiratory conditions: COPD, asthma, and respiratory abnormalities. Each of these conditions is estimated using both a Poisson and an IV regression (panels A and B, respectively). In addition, the lag structure of the effect of PM10 is examined, allowing for up to 3 lags in the analysis. Unlike Table 3, Table 4 only reports our regression coefficient of interest, which describes the effect of PM10 on hospital admissions. Therefore, every cell in the table reports the coefficient of interest which is a result of a different regression model. For example, the uppermost cell to the left (column 1, row 1) presents the immediate effect (lag=0) of PM10 concentrations on COPD admissions, in a Poisson regression. As seen in Table 4, COPD is the illness most strongly associated with PM10, both in the Poisson and IV regressions. This is especially true for a specification with no lags, where the coefficient equals 0.01 (column 1, row 1). The effect of PM10 on respiratory abnormalities is only significant in the Poisson regression and is equal to 0.006. The effect of PM10 on asthma is statistically significant for no lags or one lag in the Poisson regression, and for two lags in the case of the IV regression. Summing up the results in columns 1–3 we see that all three respiratory conditions are adversely affected by PM10 concentrations, with similar magnitudes. The IV results are similar to the Poisson regression results.

In column 4 we include the results of the effect of PM10 on abdominal pain. This is done as a falsification test for the methodology. We do not expect air pollution to significantly affect abdominal pain, and indeed we find no effect of PM10 concentrations on hospital admissions due to abdominal pain. If a significant effect was found, it would have indicated that the IV methodology is inappropriate and that sandstorms are affecting hospital admissions through channels other than PM10. Additional tests regarding the lag structure are presented in an online Appendix.

DISCUSSION

This study finds that a 10 μg/m^3 increase in PM10 concentrations is associated with a 1% increase in hospital admissions due to respiratory illnesses. The results of a standard Poisson estimate and an instrumental variable analysis using sandstorms were similar. This provides further evidence that the link between PM10 on hospitals admissions is causal in nature. The results also highlight the huge impact of sandstorms on pollution and health in Israel and suggest the need for further studies in the Middle East region, where sandstorms are common. We find that the unique setting of randomly repeating sandstorms allows for the identification of the effect that PM10 has on short-term changes in hospital admissions due to respiratory conditions.

This study contributes to the literature on the effect of PM10 on hospital admissions due to respiratory illnesses. Several studies study the effect of PM10 on asthma, showing relatively weak effects [1,2,15], while others find results within our range [3]. Studies on hospital admissions due to COPD also provide weak results [17], or within our range [15]. Finally, a recent literature review on Asian dust storms concluded that the literature contains many results that are not statistically significant or do not sufficiently control for potential confounding factors [7]. Our results are both statistically significant and tackle the issue of confounding factors and therefore add to our knowledge regarding the effect pf PM10 concentrations on hospital admissions due to respiratory illnesses.

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