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ABSTRACT

Literature has shown that air pollution can have short- and long-term adverse effects on physiological and cognitive performance, leading to adverse outcomes in the labor market. In this study, we estimate the effect of increased nitrogen dioxide (NO_2), one of the primary air pollutants, on the likelihood of accidents in construction sites, a significant factor related to productivity losses in the labor market. Using data from all construction sites and pollution monitoring stations in Israel, we find a strong and significant connection between air pollution and construction site accidents. We find that a 10-ppb increase in NO_2 levels increases the likelihood of an accident by as much as 25 percent. We observe strong nonlinear treatment effects, mainly driven by very high levels of NO_2. The probability of an accident is almost quadrupled when NO_2 levels cross into levels considered by the EPA as “unhealthy” (above the 99th percentile in our sample) compared to levels considered “clean” (below the 95th percentile in our sample). We also implement a set of instrumental variable analyses to support the causal interpretation of the results and present evidence suggestive of a mechanism where the effect of pollution is exacerbated in conditions with high cognitive strain or worker fatigue. Finally, we perform a cost-benefit analysis, supported by a nonparametric estimation and institutional information, which examines the viability of a potential welfare-improving policy to subsidize the closure of construction sites on highly polluted days.

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1. Introduction

With 9 out of 10 people worldwide breathing polluted air and an estimated death toll of seven million premature deaths each year caused by air pollution, according to the World Health Organization, research identifying and highlighting the potential effects of air pollution is in high demand. Given this, the effects of air pollution on society are a focus of a growing literature in many disciplines, including economics, that attempts to broaden the scope beyond direct health outcomes (see Aguilar-Gomez, Dwyer, Graff Zivin, and Neidell, 2022, for a recent survey).

We contribute to this literature by investigating the effects of air pollution on work accidents, which are significant and less-studied factors for productivity in the labor market. Work-related accidents, with construction workers at particular risk, cause an estimated 360,000 deaths worldwide each year and an estimated 26.5 million disability-adjusted life years (World Health Organization and International Labor Organization Report, 2021). These outcomes also translate to significant productivity losses; according to a National Safety Council (NSC) report, in the US alone, the estimated productivity and wage losses from work-related accidents totaled 44.8 billion dollars in 2020. In the EU, in 2017, the costs of work related accidents and illnesses accounted for around 3.3 percent of GDP (Elsler, Takala, and Remes, 2017).[1]

This paper presents novel and compelling evidence of the economically and statistically significant effects of air pollution exposure on workplace accidents, even at subclinical levels. We identify the effect of a primary, although less studied air pollutant, nitrogen dioxide (NO_2), on construction-related injuries and fatalities in Israel.[2] We find that a 10-ppb increase in NO_2 levels increases the likelihood of an accident by 25 percent.[3] We also observe strong nonlinear effects, with measurable effects occurring mostly at levels associated with moderate and unhealthy pollution levels, according to EPA standards, the lower bound of which corresponds roughly to the 95th and 99th percentiles in our sample. At these levels, the likelihood of

[1] Construction accidents also increase the cost of labor, due to risk compensation, and create delays that contribute to increasing costs in the housing market, a major policy issue in Israel and in many countries throughout the world (Crawford, 2021).

[2] Throughout the paper, when we discuss accidents, we refer to accidents involving an injury.

[3] We will be presenting most results in terms of a 10-unit increase, as is common in this literature. A one standard deviation in NO_2 levels in our main specification is equal to 18 ppb.

an accident is increased by 138 and 377 percent, respectively, compared to levels of clean air (below 55 ppb, the 95th percentile).

We support the causal identification by including construction site and time-fixed effects in the regressions while also controlling for other factors potentially associated with work accidents, such as wind, humidity, and temperature levels. The construction site fixed effects help us focus on within-construction site variations to control for potential permanent differences between construction sites that might affect work accidents. We also control for time factors such as day of the week, month, and year to mitigate concerns related to worker sorting and selection issues that might bias our results.

A potential challenge to our identification strategy is the possibility that pollution may be generated at the construction site itself, such that days of high/particular activity at the construction site may result in higher pollution and more accidents. We use instrumental variables to address these potential concerns of the cogeneration of pollution and accidents.[4]

We take advantage of the high density and spatial distribution of air pollution monitoring stations and instrument pollution at the nearest monitoring station and up to 1 km from the construction site, with the average pollution level measured in stations within a 5–10 km radius of the construction site. For our exclusion restriction, we rely on the assumption that even if construction sites are a source of pollution, these small levels of pollution generated by the construction site are not likely to carry to the monitoring stations located more than 5 km away. We also assume that pollution levels measured at distant monitoring stations can only affect the probability of a construction accident through pollution levels measured at the closest monitoring station to the construction site. For our second instrument, we also take advantage of the high frequency of measurements of pollution in our data (8-hour intervals of the average of 5-minute readings, each day, between midnight and 8 a.m., 8 a.m. and 4 p.m., and 4 p.m. and midnight). We use as an instrument for pollution the lagged pollution levels measured at the monitoring station in the intervals

[4] We also use data on wind direction to limit our sample to days on which the wind was blowing from the monitor to the construction site. By limiting the potential threat of pollution from the construction site being picked up by the monitor, we provide supportive evidence for the robustness of our results to the possible codetermination of other factors generating pollution at the site and increasing the probability of an accident at the same time.

of the evening and the night before, when activity at the construction site itself is minimal. For our exclusion restriction to hold, we assume that any pollution generated by the site itself cannot alter pollution levels measured the night before when the site is, by and large inactive. Further, these pollution levels, measured during the night before, should only affect the probability of a construction accident occurring in each site through pollution levels measured during working hours on the day itself.

Our instrumental variable results are consistent with our main findings, as a 10-unit increase in NO_2 levels increases the likelihood of an accident by 28 percent and 31 percent for the geographical proximity and lagged IVs, respectively. We further show that the findings are robust to using the general air quality index (AQI), which includes an index of the six major pollutants (NO_2, $PM_{2.5}$, PM_{10}, O_3, CO, and SO_2) instead of NO_2 as the instrumented variable. This analysis relieves concerns regarding the possibility of under-identification due to the multiplicity of pollutants that might be both highly correlated with the instrumented pollutant and potentially directly affect the outcome variable.

As a next step, we focus on the potential mechanisms of the effect. By examining the interaction of NO_2 levels with worker fatigue (proxied by day of the week) and with cognitive stress (proxied by high levels of wind speed, temperature, and humidity), we provide suggestive evidence that the detrimental effect of NO_2 on accidents is exacerbated in conditions of strenuous physiological states of the workers. Our setting and the finding linking the effects of pollution with cognitive strain may provide suggestive evidence of the importance of pollution exposure in mentally and physically strenuous settings beyond construction site work, such as those of first responders, physicians, and other high-stakes professions.

To demonstrate the significance of our econometric strategy for proper identification, we show the importance of focusing on a detailed geographical level of analysis, such as the construction site level, to avoid issues of endogeneity. We demonstrate that the effects of particulate matter and high temperature, which have been linked to increased levels of accidents in previous studies that looked at larger geographical units, do not persist when we control for construction site fixed effects, while the effect of

NO_2 remains robust.[5] We also illustrate the importance of monitoring pollution in proximity to the unit of analysis to avoid measurement error attenuation bias. We demonstrate this by showing how the effect size and significance decrease when we gradually relax the restriction on the construction site sample to include sites for which the maximum distance from a construction site to the closest monitoring station is increased from 1 km to 1.5, 2, 5, and any distance, respectively.

We conduct a cost–benefit analysis to determine the viability of subsidizing a shutdown of construction sites at times of extreme pollution. Using a nonparametric estimation strategy, we find the maximum level of subsidy, conditional on local pollution levels, that the government can offer to each contractor to shut down their daily operations. We find that the policy might become relevant only for very high pollution levels when the probability of an accident is high enough that the expected benefits from avoiding worker's insurance payouts are large enough to offset losses from construction site shutdown costs for the day.

The rest of the paper is organized as follows. In Section II, we present a review of the relevant literature and the contribution of our study. Section III presents institutional information in the Israel context and our data. Section IV presents our empirical strategy. In Section V, we present our empirical results. Section VI presents our robustness checks. Section VII discusses potential mechanisms and present results related to other potential determinants of construction accidents. Section VIII presents our cost-benefit analysis, and Section IX concludes.

2. Related Literature

Physicians and epidemiologists have mainly examined the direct health effects of air pollution on health outcomes. They find that even short-term exposure to low levels of pollution might affect the cardiovascular and respiratory systems (Brook and Rajagopalan, 2007; Viehmann et al., 2015) as well as brain functioning (Forman and Finch, 2018), which in turn may cause fatigue, impaired motor function,

[5] We also show suggestive evidence that the effect of NO_2 is not driven by its potential codetermination with other pollutants.

lack of concentration, and impatience (Siegel and Crockett, 2013; Delgado-Saborit et al., 2021). These physiological outcomes provide potential mechanisms compatible with our findings, as fatigue and lowered cognition caused by pollution might increase the likelihood of a construction accident.

More recent literature has focused on the economic effects of air pollution. Researchers have found that short-term exposure to air pollution decreases work productivity (Graff Zivin and Neidell, 2012; Chang et al., 2016), reduces labor supply (Aragón et al., 2017; Hanna and Oliva, 2015; Holub et al., 2021), and has adverse effects on human capital formation (Ebenstein, Lavy, and Roth, 2016).

Our paper adds to this literature by examining the effects of air pollution on a less studied but significant factor affecting labor outcomes, workplace accidents. We also focus on a less studied, although ubiquitous, air pollutant, nitrogen dioxide. The paper most closely related to ours is that of Vega-Calderón et al. (2021), who found a connection between increased levels of PM_{10} and NO_2 and workplace accidents in Madrid, Spain. Our study goes further by including controls for humidity levels, site fixed effects, and an instrumental variable analysis, which allow for a causal interpretation of the findings. Furthermore, we find significantly stronger effects of air pollution, perhaps due to the higher accuracy of pollution level measurements at construction sites facilitated by the large number and high density of monitoring stations and construction sites in our data. The increased accuracy decreases the likelihood of measurement error bias in our results.

3. Institutional Information and Data

Our dataset is a combination of data from three primary sources: the Israeli Ministry of Economy and Industry, which provided us with construction sites' locations, activity dates, and construction accidents that occurred between 2017–2019; the Israeli Ministry of Environmental Protection, which provided us with measures of air pollution and weather for those years; and Kav LaOved, a nonprofit organization focused on workers' rights, which provided us with complementary construction site accident data.

a. Construction Sites and Accidents Data

The initial construction site sample provided by the Ministry of Economy and Industry included 25,571 construction sites active in Israel between 2017 and 2019.[6] Using geo-coding techniques, we matched the sites' addresses to coordinates. Knowing each site's opening and closing days, we assigned an observation to each active day for each site, which resulted in our final sample of 24,614 sites and 10,016,000 observations.[7]

The accident sample provided by the Ministry of Economy and Industry included 1,316 accidents during the sample period. The accidents provided by Kav LaOved did not include site IDs matching the ministry's data. So we matched the accidents to the sites by their address instead, which resulted in an additional 31 accidents. Merging the dataset of the site's active days sample and the accidents sample, we were left with 1,164 accidents per 10,016,000 working days in construction sites.[8]

Figure 1 shows the distribution of construction sites across Israel. Dividing Israel's inhabited areas by construction sites active in our sample yields approximately one construction site per 0.28 km^2. The lifespan of each construction site in our data varies between a day and six years; the average is approximately a year and a half.

As for the accidents, as shown in Figure 2, we can see that construction accidents occur across all days of the week, with a substantial drop on Fridays and Saturdays.[9] As the yearly average of workers in Israel's construction sector was around 272,500 during the sample period, the yearly accident rate resulted in 161 accidents per 100k workers.[10]

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[6] A construction site is defined as a location where construction or engineering work is being done that requires the consent of a registered engineer. Painting, flooring, and other renovations are not included.

[7] For our main specification we use the interval from 8 a.m. to 4 p.m., which corresponds to the working hours of each site. The decline in the number of sites is due to lack of exact matching of 957 sites' addresses in the geo-coding process.

[8] Accidents reported by the Ministry of Economy and Industry are those reported under Israel's Occupational Accidents and Diseases Ordinance. The law requires employers to promptly notify the regional labor inspector of any workplace accident that causes an employee to be incapacitated for at least three days.

[9] The work week in Israel starts on Sunday, while Friday and Saturday are weekend days, equivalent to Saturday and Sunday in most of the western world.

[10] There appears to be some underreporting of nonfatal construction accidents in Israel, as the average yearly accident rate in in the US and the EU for the same time period was 1,040 and 3,270 per 100k workers respectively (Center for Construction Research and Training, 2022; Eurostat, 2022). There is no indication that this underreporting is related to pollution levels and could only potentially reduce the statistical power in our analysis.

b. Environmental Data

Air pollution and weather data were provided by the Israeli Ministry of Environmental Protection, which reported an 8-hour average of 5-minute interval readings of NO_2 (ppb), wind strength and direction (m/sec and degrees, respectively), temperature (c°), humidity (%), as well as other pollutants at 173 monitoring stations throughout Israel for the sample period. The locations of monitoring stations are spread out across the country, as seen in Figure 1. Monitoring stations in urban areas account for 37 percent of all monitoring stations, rural for 30 percent, and suburban for 11 percent. Monitoring stations near trains/roads account for 18 percent and industrial areas for 4 percent.

Each active day in a construction site is assigned the nearest reading for each variable, where 21,861, 15,440, 12,677, and 7,199 construction sites have at least one monitoring station at a 5, 2, 1.5, and 1 km distance, respectively. Unfortunately, the other major pollutants were not as consistently measured as NO_2, possibly due to the relatively simple and cost-effective nature of NO_2 monitors, which limited our ability to reliably examine their effects due to the small sample size.[11]

The primary source of NO_2 pollution is fuel combustion from transportation and industrial work, with transportation alone accounting for nearly 94 percent of NO_2 emissions in population centers in Israel, according to the Israeli Ministry of Health. NO_2 levels vary significantly over space and time, with high concentrations measured near major roads, intersections, and highways during rush hours dissipating with distance and time. Figure 3 illustrates the variation of NO_2 in our sample from several monitoring stations in the Central District in Israel. The figure, composed of a matrix of maps, depicts NO_2 levels at each monitoring station over all three 8-hour intervals each day, vertically and horizontally across all days of the week for a randomly chosen week in January 2018. As shown, NO_2 concentrations are significantly higher near major roads and decrease with distance. Furthermore, as expected, a significant drop can be observed during the night and on weekends when traffic volume is reduced.

[11] See the robustness section for an analysis including other pollutants.

Table 1 shows summary statistics for pollution and weather variables in our dataset. In 2017, the European Environmental Agency reported an annual mean average of 22.0 µg/m3 for NO_2 across the European Union states,[12] while the yearly average in the US was 15.5 µg/m3, according to data from the EPA. Converting our data from ppb units to µg/m3 at 25 degrees Celsius and 1 atm (standard atmospheric pressure) results in a mean of 20.9 µg/m3 across that exact timespan. According to the Israeli Clean Air Act passed in 2008, Israeli standards and recommended levels of air pollution are precisely those set by the European Union and very similar to levels in the US and those recommended by the WHO.[13]

4. Econometric Strategy - Identification

a. Baseline Linear Probability Model

In our primary specification, we examine the partial correlation between NO_2 levels and construction accidents using a linear probability fixed effects model:

$$Y_{st} = \alpha + \beta NO_{2st} + f(Temp_{st}, Wind_{st}, Hum_{st}) + S_s + DMY_t + \varepsilon_{st}, \qquad (1)$$

where *s* indexes the construction site and *t* the day. Y_{st} denotes the probability of an accident, NO_2 is the level of nitrogen dioxide measured in ppb units at the monitoring station closest to the construction site (up to 1 km). The equation includes construction site fixed effects S_s and time fixed effects DMY_t (day of the week, month, and year). $f(Temp_{st}, Wind_{st}, Hum_{st})$ are weather variables (temperature, wind speed, and humidity levels, respectively), and weather squared measured at the closest monitoring station. ε_{st} is the idiosyncratic error term. Standard errors are clustered at the construction site level.

There are several potential threats to inferring a causal relationship between pollution and construction accidents estimated by equation (1), β , mainly concerning endogeneity, measurement, and selection (see Graff Zivin and Neidell, 2013, for a review). First, the endogeneity of pollution levels is

[12] Data is from a 2019 report by the European Environmental Agency: https://www.eea.europa.eu/data-and-maps/daviz/annual-mean-no2-concentration-observed-7#tab-googlechartid_chart_21 (accessed July 17, 2022).
[13] The threshold level in excess of which is considered a violation is 200 (40) for Israel, the EU, and the WHO and 188 (98) for the US, for hourly (yearly) µg/m3 averages (Negev, 2022).

potentially a major concern. Endogeneity may arise due to pollution levels potentially being confounded with other environmental factors, such as temperature, wind, or humidity levels, which could affect the probability of an accident. We attempt to deal with this issue by flexibly controlling for the weather variables in our regression function.

Another potential source of endogeneity is that the probability of accidents might be permanently higher in specific construction sites compared to others, which might be correlated with pollution levels. This could be the case if pollution levels are higher in regions where the construction contractors have lower safety standards or if lower-level, less experienced, or, more generally, prone-to-accident workers choose or are selected to work in regions with higher pollution levels. We attempt to mitigate these selection issues by adding construction site fixed effects to our estimation equation, which allows us to focus on within-construction site variation in pollution levels and probabilities of an accident. We also add a day of the week, month, and year fixed effects, mitigating concerns related to temporal patterns in accident probability that might be correlated with pollution levels (e.g., selection of workers or activities in the construction site by day of the week, the season of the year, or specific ethnic holidays or rest days, all of which might have persistent differences in pollution levels as well).

Another potential issue in the literature evaluating air pollution impacts is of measurement error. When either the density of monitoring stations or the frequency of measurements is low, the potential for measurement error biasing our results is high. To address this, we take advantage of a large number of monitoring stations and their geographic spread across the country and restrict the observations of construction sites to those with a monitoring station up to 1 km away. We also use the fact that we have an average reading of pollution levels in three different intervals per day and choose the pollution levels in the time interval corresponding to work hours, between 8 a.m. and 4 p.m. These measures allow us to reduce the random noise, which can lead to attenuation bias, and increase the likelihood of estimating the true magnitude of the effects of pollution on construction accidents.

Finally, the issue of avoidance behavior has been emphasized in the literature examining the effects of pollution (Aguilar-Gomez, Dwyer, Graff Zivin, and Neidell, 2022). Ex-ante avoidance, in our case, can occur if workers decide not to show up to work on days of high pollution; this can also bias our results in the potential case where the more careful workers, those less prone to accidents, exhibit such avoidance behavior more frequently than less cautious workers. This possibility is implausible as the number of workers is inelastic to pollution levels, and our institutional information indicates that workers and contractors are not likely to be aware of the specific impacts of air pollution on accidents or act upon them.[14] The avoidance behavior is even less likely to occur in any asymmetric way related to proneness to accidents.[15]

b. Instrumental Variables

Although our primary specification strategy in the previous section captures a significant part of the potential threats to the causal interpretation put forward in the literature, there might still be several concerns that can potentially bias our results. One such concern might be that high levels of pollution from the construction site itself if happening on busy or specific days when the likelihood of an accident increases, might also drive our results. We implement an instrumental variable approach to deal with this potential concern and mitigate similar scenarios of endogeneity.

First, we instrument pollution levels at the closest monitoring station (i.e., within a radius of at most 1 km from the construction site) with the average pollution levels measured in stations within a 5–10 km radius. We assume that any potential pollution generated at the construction site itself would be too small to meaningfully affect measurements at monitoring stations more than 5 km away (Dragomir et al., 2015; Fuller, Carslaw, and Lodge, 2002). To further support this claim, we make use of a construction company's limited liability status, a proxy for construction site size, and find no evidence that large-sized construction sites affect pollution in this range.[16] We also assume that pollution levels measured at more distant

[14] Checking the correlation between monthly workers in Israel against the mean nitrogen dioxide levels, we find no evidence of such avoidance behavior, as the correlation is -0.055.
[15] See also Salehi Sichani, Lee, and Robinson Fayek (2011), who find no correlation between tenure at work and absenteeism in the industrial construction workforce.
[16] In Appendix Table A1, we present results when regressing the nitrogen dioxide level in the closest monitoring station (within 1 km) on the average level of this pollutant in a 5–10 km radius, first for the sample of smaller

monitoring stations cannot directly affect the probability of a construction accident beyond their effect through pollution levels measured at the monitoring station closest to the construction site.

The second instrument we use is lagged pollution levels measured at the closest monitoring station to the construction site from the interval of the night before. As in the case of the previous instrument, we assume that pollution levels measured the night before can only affect the probability of a construction accident occurring at each site during working hours on the day itself solely through the pollution measured during those working hours. We also work under the more straightforward assumption that any pollution generated by the site itself cannot affect pollution levels measured the night before when the site is predominantly inactive.

Formally, our instrumental variable analysis is represented by

First stage:

(2) $$NO_{2st} = \alpha + \lambda NO_{2s,t-0.5} + f(Temp_{st}, Wind_{st}, Hum_{st}) + S_s + DMY_t + \nu_{st},$$

(3) $$NO_{2st} = \alpha + \delta NO_{2g_{5-10km}(s),t} + f(Temp_{st}, Wind_{st}, Hum_{st}) + S_s + DMY_t + \nu_{st},$$

Second stage:

(4) $$Y_{st} = \alpha + \beta \Pr ed(NO_{2st}) + f(Temp_{st}, Wind_{st}, Hum_{st}) + S_s + DMY_t + \varepsilon_{st},$$

where we instrument pollution levels at the monitoring station closest to the construction site *s* first in equation (2) with lagged NO_2 levels measured at the same monitoring station from the interval of the night before ($NO_{2s,t-0.5}$) and second in equation (3) with the NO_2 levels measured by the average of stations in a 5–10 km radius of the construction site ($NO_{2g_{5-10km}(s),t}$). $\Pr ed(NO_{2st})$ are the values of NO_2 predicted in the first-stage equations (2) and (3).

construction sites and then for the sample of bigger construction sites. We find that these estimates are not statistically significantly different from each other.

c. Nonlinear Effects

International organizations and governments have generally set standards and guidelines focused on exposure to high levels of air pollution. This is partly because the literature on the physiological effects of pollution has highlighted the detrimental health effects of exposure to high pollution levels, while not focusing on the potential effects of lower-level exposure. This may either be due to the lack of ability to measure subclinical health effects of exposure to lower pollution levels or due to the potential nonlinear impact of pollution. The economic literature has focused less on nonlinear effects when examining the effects of air pollution.[17] In this section, we investigate whether there are nonlinearities in the effect of pollution levels on the probability of construction accidents.

We start by focusing on high levels of air pollution. To examine the effect of high pollution levels, in equation (5), we substitute the continuous measure of air pollution in equation (1) with dummy variables for clean, moderately polluted, and highly polluted days. We define moderately polluted days as days when NO_2 levels are higher than 53 ppb, corresponding roughly to the 95[th] percentile in our sample, which the EPA defines as moderate pollution. We define highly polluted as days when NO_2 levels are higher than 100 ppb by EPA standards, corresponding roughly to the 99[th] percentile in our sample.[18] Formally,

$$(5) \quad Y_{st} = \alpha + \beta ModerateNO_{2st} + \delta HighNO_{2st} + f(Temp_{st}, Wind_{st}, Hum_{st}) + S_s + DMY_t + \eta_{st},$$

where $ModerateNO_{2\,st}$ is a dummy variable equal to 1 when NO_2 levels are between 53 and 100 ppb, and $HighNO_{2\,st}$ is a dummy variable equal to 1 when pollution levels exceed 100 ppb.

Next, we aim to expand our focus beyond extreme pollution levels and have a more general outlook on the progression of the effect of air pollution on construction work accidents. For this purpose, we take advantage of the large number of observations and monitoring stations and their geographical spread, which generates sufficient variation to allow us to employ nonparametric estimation strategies to examine

[17] See Arceo, Hanna, and Oliva (2016) and Hanlon (2018) for some notable exceptions.
[18] The United States Environmental Protection Agency's (EPA) air quality guide for nitrogen dioxide classifies NO_2 levels into 6 groups (in ppb units). Good: 0–53, Moderate: 54–100, Unhealthy for Sensitive Groups: 101–360, Unhealthy: 361–649, Very Unhealthy: 650–1249, and Hazardous: 1250+.
https://www.airnow.gov/sites/default/files/2020-05/aqi-technical-assistance-document-sept2018.pdf

the effects of air pollution on accidents in the entire distribution. We implement a kernel semi-parametric regression model (Robinson, 1988; Gau, Liu, and Racine, 2015), i.e.,

$$Y_{st} = \alpha + H(NO_{2st}) + f(Temp_{st}, Wind_{st}, Hum_{st}) + S_s + DMY_t + \eta_{st} , \quad (6)$$

where $H(NO2_{st})$ is a local linear 2nd-order Gaussian kernel function with least squares cross-validated bandwidth selection and bootstrap confidence intervals (Li and Racine, 2004; Hayfield and Racine, 2008)

5. Results

We begin by presenting the results for our baseline linear probability model presented in equation (1). In Table 2, columns (1) and (2), we report the correlation between a continuous measure of NO_2 using OLS without controls and with controls for weather and time and site fixed effects, respectively. We estimate that a 10 unit increase in NO_2 levels is associated with an increase in the probability of an accident by 0.000033 percentage points (SE=0.000012) and 0.000039 percentage points (SE=0.000011) with and without controls, respectively, which translates to a 25 percent and 30 percent increase in the probability of an accident compared to mean levels or to an increase of 0.031 in the number of accidents per 100,000 workers each year. Both estimates are significant at the 1 percent level. We can observe that adding controls substantially reduces the magnitude of our estimate. This indicates that endogeneity arising from confounding with other environmental factors and selection issues associated with site location and timing of work is a valid concern when attempting to estimate the effects of pollution.

In columns (3) and (4) of Table 2, we add the results of our instrumental variable estimation presented in equations (2)–(4). We estimate that a 10 unit increase in NO_2 levels is associated with an increase in the probability of an accident by 28 percent (SE=13 percent) and 31 percent (SE=12 percent) when instrumenting for NO_2 pollution levels at the closest monitoring station with pollution levels from the average of the pollution level measured from stations at a radius of 5–10 km from the construction site and when instrumenting with lagged NO_2 levels at the monitoring station from the night before, respectively.

The estimated effect of pollution when using the IV of lagged pollution levels remains significant at the 1 percent level, while the estimate when using the IV of the pollution level measured from stations at a radius of 5–10 km is significant at the 5 percent level.[19] The first stage for both instruments is strong, with an F statistic of 1435 and 1855, respectively.[20] We observe that our 2SLS estimates are similar to our OLS coefficients, indicating that the threat of endogeneity, after flexibly controlling for weather variables and adding site and time-fixed effects, might not be a major concern.

Next, we present the results where we examine whether NO_2 pollution has a nonlinear effect on the probability of construction accidents. In column (5) of Table 2, we focus on high pollution levels and present the results where we use specifications including the dummy variables of moderate and high pollution levels (between the 95th and 99th percentile and above the 99th percentile of NO_2 levels, respectively), as specified in equation (5). The results suggest that we have a nonlinear relationship, where very high levels of NO_2 pollution increase the probability of an accident to a higher degree compared to moderately high levels, relative to days with clean air. A shift from clean air to moderately high pollution levels is associated with an increase of 0.000159 percentage points (SE=0.0001076) in the probability of an accident, which translates to an increase of 138 percent, but it is not statistically significant at conventional levels, while a shift from clean air to high levels of pollution is associated with an increase of 0.000433 percentage points (SE=0.000172), which can also be translated to an increase of 377 percent or to 4.06 more accidents per 100,000 workers each year, and is statistically significant at the 5 percent level.

In Figure 4, we present the results of our semiparametric specification described in equation (6). We observe a convex nonlinear relationship where the increase in the probability of an accident is relatively small when pollution levels increase for lower levels of NO_2. The increase in probability gradually becomes

[19] The results are robust to using different cutoffs of the radius.
[20] The results are very similar (27% and 28%) and are significant at the 1% level when we add the instrument of lagged pollution levels from the evening before (4 p.m. to midnight) to the equation with the instrument of lagged pollution levels from the night before (midnight to 8 a.m.) that we use in equation (2), and when we combine the lagged instruments with the IV of the pollution levels measured from stations at a radius of 5–10 km.

larger for increasingly higher levels of NO_2. As seen in Figure 4, the marginal effect of an increase in pollution levels becomes larger than our OLS estimate around the 95th percentile and steeper with the increase in NO_2 levels. The predicted probability of an accident surpasses that of our linear model, starting at very high levels of NO_2 (larger than the 97th percentile), which is consistent with our high pollution dummy variable results presented above. These findings indicate that our results are primarily driven by the increased likelihood of accidents on highly polluted days, suggesting that the impact of pollution on construction accidents is mostly relevant on days with very poor air quality.[21]

6. Robustness

In this section, we report a set of robustness tests to further validate the findings on the effects of NO_2 pollution on the probability of accidents. First, in columns (1)–(4) of Table 3, we present evidence that the effect size and significance are reduced when we allow for measurements of pollution from monitoring stations that are further away from the construction site. In our main analysis, we restrict our observations to construction sites for which the closest monitoring station for pollution levels is up to 1 km away, in columns (1)–(4), we increase this range to 1.5, 2, 5, and any distance, respectively. We can see a continuous decrease in both the effect size and significance levels, suggesting both that the effect is indeed related to pollution levels present in the close vicinity of the construction site instead of a general regional effect and that measurement error generated due to the distance between the measurement sensor and the area where the effect occurs is indeed a concern to be mindful of when attempting to estimate the effects of pollution.

A major concern when instrumenting for a specific pollutant is the possibility of under-identification due to the multiplicity of pollutants that might be both highly correlated with the instrumented pollutant and potentially have a direct effect on the outcome variable (Benmarhnia, Bharadwaj, and Romero, 2022; Aguilar-Gomez, Dwyer, Graff Zivin, and Neidell, 2022). We believe this issue is less of a concern in our

[21] The results are consistent and remain significant when we use NO instead of NO_2 as our measure of pollution and are presented in Table A2 of the online appendix. We chose to focus on NO_2 because it is the component of greatest concern for adverse effects and is used as the indicator for the larger group of NOx (U.S. Environmental Protection Agency, 2011).

specification, as both our instrumented variable and our instruments rely on levels of NO_2, either lagged or at proximate measurement stations, increasing the likelihood that the effect of the instrument on accidents is mostly through the same pollutant. This would decrease the possibility of under-identification, compared to a general instrument which might more likely affect accidents through different pollutants. To further support the case against this under-identification, compute a general air quality index (AQI), a commonly used overall index measure that includes NO_2 and the otherfive5 major pollutants ($PM_{2.5}$, PM_{10}, O_3, CO, and SO_2). As mentioned, our sample size for the other pollutants is small compared to NO_2. Nevertheless, suppose we find similar results when we instrument for the general AQI compared to instrumenting for NO2. In that case, we can consider this as suggestive evidence that under-identification is less of a concern in our context. This is due to the ability of the AQI to capture the independent effect of each pollutant. As can be seen in columns (6) and (7) of Table 3, our results are consistent with our primary IV outcomes when we use both the lagged and the geographical proximity instruments, albeit noisier likely due to the smaller sample size.

Next, we attempt to mitigate concerns regarding the codetermination of pollution levels and accidents potentially resulting from pollution from construction sites to the closest monitoring station. As the wind's direction can be a determining factor in the spatial distribution of pollutants, we run our baseline model in equation (1) after restricting our sample to days where the general wind direction is blowing from the monitor to the construction site. By excluding days where the wind direction is in the range of a 90-degree angle to each side from the construction site to the monitor, we rule out the possible codetermination of other factors generating pollution at the site and increasing the probability of an accident at the same time. We report in column (5) of Table 3 the results of this specific exercise and compare them to our main specification. The results remain robust in size and significance.[22]

In column (8) of Table 3, we present a multiple treatment analysis where we regress the probability of an accident on both the NO_2 levels and a general AQI measure excluding NO_2. We find that the coefficient

[22] The results remain unchanged when we use specifications with different ranges of wind direction angles. The results are not presented and are available from the authors upon request.

for NO_2 remains strong and significant while the coefficient for the general AQI is close to zero. This result further supports our hypothesis that exposure to NO_2 rather than other potential covariates, such as other pollutants, is driving our results.[23]

By nature, pollution is correlated over time and space, which might lead to spatial autocorrelation of the pollution at hand. In Appendix Table A3, we show that our results remain robust while accommodating for this issue in two different ways. First, we report Conley-adjusted standard errors for our main Table 2 specification. By applying this method, we address both the autocorrelation of pollution levels based on a construction site's location and pollution that might remain in the air over certain time intervals (Conley, 1999). Second, as construction sites are assigned to their closest monitor's reading within 1 km, as a robustness check, we report for our main specifications the clustered standard errors also at the monitoring station level. This allows us to take into account the actual location where the pollution was estimated. All our results remain statistically significant in both cases.

7. Mechanism and Other Determinants

As a next step, we aim to identify whether pollution has different effects depending on the physiological state of the worker. By doing so, we may better understand the potential mechanisms that underlie the effects. To infer the potential effects of these changes, we use indirect evidence since workers' individual information is not available in our data. Polish, Sin, and Stillman (2020) found that more occupational accidents occur at the start of the work week and provide suggestive evidence that weekend fatigue might be a responsible factor.

According to Figure 2 Panel A, our data displays a similar pattern. Sunday, the start of the working week in Israel, has a significantly higher accident rate. Thus, by adding the day-of-the-week dummy variables with NO_2-level interaction terms to our primary specification presented in equation (1), we can examine whether there is a differential effect of pollution on the probability of an accident depending on

[23] We caution that this analysis is only suggestive as NO_2 and the other pollutants might be endogenous, and the number of observations with information on other pollutants is smaller than in our main specification.

the level of fatigue. As we can see in column (8) of Table 4, pollution has a significantly greater effect on Sundays than on other working days. These results suggest that a potential channel for pollution's detrimental effect on accidents may be related to worker fatigue or lack of cognitive awareness and that this effect might be exacerbated when these factors are present even before the worker is exposed to pollution.

Likewise, extreme weather conditions such as strong winds, high temperatures, and humidity can be other causes for a high cognitive load or physical strain that puts workers at greater risk.[24] The effect of these already difficult conditions might be exacerbated by high levels of pollution.

As seen in columns (2)–(7) of Table 4, pollution does play an increased role when wind strength, temperature level, and/or humidity level are above the 75th percentile in contrast to the more mild conditions where levels are below the 75th percentile.[25] These findings also highlight the transitory, short-term nature of the effect of exposure to NO_2.

In this paper, we choose to focus mainly on the effects of nitrogen dioxide for several reasons. First, NO_2 is more accurately measured in our sample than other pollutants, due to the larger number of monitoring stations that have data on this pollutant in our period. This allows us to estimate our results more accurately at a larger number of locations across Israel. The second advantage of NO_2, compared to other pollutants, is that it introduces significant spatial variability, which allows us to capture the effect more precisely (Hewitt, 1991). Nevertheless, the effect of ambient air and weather variables on short-term outcomes has been studied using several other determinant factors (e.g., Sager, 2019; Burkhardt et al., 2019). In particular, fine particulate matter ($PM_{2.5}$) and temperature have been specifically linked to workplace accidents (Chambers, 2021; Jisunge et al., 2021). Taking this into account, we present suggestive

[24] As the wind becomes stronger, accidents such as falling from a height, being hit by objects carried by the wind, small particles flying into one's eyes, etc., become more frequent. Hot and humid weather conditions can raise the body's core temperature and cause a multitude of adverse effects such as muscle cramps and heat exhaustion.

[25] The specification includes all the controls from our main analysis and we do not find consistent differences in median pollution levels between observations above and below the 75th percentile. This similarity limits the possibility that other factors such as correlated weather conditions or the nonlinearity of our main effect may account for our findings.

evidence on the effects of these determinants in our sample while also taking advantage of the high density and spatial distribution of air pollution monitoring stations in our sample to examine the importance of potential endogeneity threats biasing results when attempting to estimate the effects of environmental variables.

Many of these studies mentioned above analyze data in large geographical units, such as the county or ZIP code level, while also sometimes neglecting relevant variables such as time, weather, and the work site's unique characteristics and determinants. In Appendix Tables A4 and A5, we show that when controlling for only limited specifications, as done in previous research, our results are also significant for the effect of temperature and $PM_{2.5}$ on workplace accidents. For $PM_{2.5}$, our results are similar in size to those found in our main NO_2 analysis, even after we control for city-fixed effects. These effects do not persist when measured precisely. When we incorporate construction site fixed effects, the effects of both determinants are drastically reduced both in size and significance and are no longer present.

In light of these results, caution should be exercised when conducting similar analyses. Omitting relevant time and weather variables and, perhaps more importantly, not controlling for fixed effects at a more detailed geographical level of analysis, such as the construction site level, might lead to an endogeneity issue that can bias the results.[26]

The fact that our results for the effect of NO_2 on construction site accidents remain robust to different specifications, whereas we do not find a similar effect of $PM_{2.5}$ exposure in our main specification raises an important question about the potential reasons and mechanisms behind these differential effects of the two pollutants. Although evidence is generally sparse, some prior research on the effects of NO_2 and $PM_{2.5}$ identified potentially differentiated effects of each pollutant on components of performance domains such as executive function, visuospatial ability, semantic fluency, and more (Wang et al., 2021; Sakhvidi et al., 2022). As the differences in the mechanisms of the effect of each pollutant on human activity remain a

[26] While examining these other determinants is not the main focus of our paper, for the sake of robustness, in Appendix Table A3, we present the results of our main specification examining the effects of NO_2 when applying the sharpened false discovery rate (FDR) method to adjust for potential multiple hypothesis testing issues. Our results remain statistically significant following this adjustment.

puzzle, new findings, such as the findings of our research, can contribute to our understanding of the differentiated impact of each pollutant.

8. Cost–Benefit Analysis

Policymakers can mitigate the detrimental effects of pollution in several ways. Reducing pollution levels through the limitation of the allowed levels of emission, raising public awareness, facilitating mitigation of pollution through avoidance behavior, and improvements in treating its negative effects are some of the potential focus areas of relevant interventions. In this section, we focus on policy related to facilitating the mitigation of pollution through avoidance behavior. We incorporate our findings on the effects of pollution on the probability of accidents with reports from the Ministry of Finance, the National Insurance Institute (NII), and the Central Bureau of Statistics on the costs to the government due to construction accidents and the costs of construction site closures. Then we run a back-of-the-envelope calculation on whether it might be beneficial for the government to subsidize construction site closures on days with high pollution levels, and estimate the amount of subsidy and the associated threshold levels of pollution for which this potential policy should apply.

The National Insurance Institute of Israel (NII) insures all legal workers in Israel and is the sole payer of compensation costs for lost wages or income due to a workplace accident. The one-time compensation paid by the NII while workers are absent is calculated as 75 percent of the insured worker's income in the previous three months, with payments continuing for up to 13 weeks. Also compensated by the NII are any additional immediate or long-term expenditures such as disability payments, dependent pensions, and physiotherapy and rehabilitation fees, which are all determined based on the severity of the accident.

The expected costs saved for the government from a shutdown of a construction site on a certain day conditional on the local NO_2 level can be calculated using the following formula:

(7) $E(\mathrm{cos}ts \mid NO_2) = P(Accident \mid NO_2) \times \mathrm{Cos}ts_{Accident\_Insurance}$,

where $P_{Accident}$ is the average probability of an accident for the day given local NO_2 levels, and $Costs_{Accident\_Insurance}$ is the costs of insurance paid out per injury by the government. This is a conservative assessment as it does not include the productivity losses generated by the injury or any potential negative externalities caused by the injury. According to data from the NII, the estimated lifetime costs of insurance payment per injury by the government sum up to an average of approximately 3.681 million NIS[27] per injury. This estimation was calculated by summing up one-time payments ($P_1 = 715\ million\ NIS$) and yearly payments of all life-long payments ($P_2 = 5{,}372\ million\ NIS$)[28] multiplied by the difference between the average life expectancy ($Age^e = 83$) and the average age of the injury[29] ($\overline{Age} = 39$). This sum is then multiplied by the percentage of accidents that are a direct cause of construction site accidents[30] (p_con = 10.7 percent). Eventually, this sum is divided by the number of construction injuries the agency pays for in a year (6,892). This calculation yields a total cost of approximately 3,681,000 NIS per injury. Formally this calculation is given by:

$$(8)\quad \text{Costs of accident insurance} = \frac{(P_1 + (P_2 \times (Age^e - \overline{Age})) \times p\_con)}{Injuries}.$$

Plugging the total costs per injury into equation (7), we can estimate that the expected cost savings to the government from closing the construction site for the day is $P_{Accident} \times$ 3.681 million NIS. Given this potential expected savings from injury avoidance, we can calculate the threshold amount of subsidy the government can offer a construction site to shut down for the day, given the expected local pollution

[27] The conversion rate between the Israeli currency, namely the New Israel Shekel (NIS), and the US dollar is 3.46 to 1 as of July 17, 2022.

[28] From a report by the National Insurance Institute: https://www.btl.gov.il/Publications/Skira_shnatit/2020/Documents/chap-3-08-avoda.pdf (accessed September 29, 2022).

[29] From a report by the Israeli Parliament Research and Information Center analyzing data from the NII and the Ministry of Economy and Industry: http://fs.knesset.gov.il/%5C20%5CCommittees%5C20_cs_bg_341116.pdf (accessed July 17, 2022).

[30] From a report by the Israeli Parliament Research and Information Center analyzing data from the NII: https://fs.knesset.gov.il/globaldocs/MMM/2d596b58-e9f7-e411-80c8-00155d010977/2_2d596b58-e9f7-e411-80c8-00155d010977_11_7328.pdf (accessed July 17, 2022).

level in its vicinity. Each contractor can then decide whether it is beneficial to accept the offer given its incurred costs from closing down the site for the day.[31] Finally, we can use the results of this study to estimate the average probability of an accident in a construction site given the level of NO_2 in its vicinity.

Given the observed nonlinearities in the connection between pollution levels and the probability of an accident, Figure 5 presents a nonparametric estimation similar in its approach to equation (6). By implementing such a strategy, we predict the probability of an accident more accurately across the different levels of pollution to further suggest a more precise monetary subsidy based on pollution levels. In Table 5, we present a range of NO_2 levels, their corresponding average probability of an accident, and the associated maximum subsidy amount beneficial for the government to offer contractors to shut down the construction site for the day.[32] For example, at 53 ppb (approximately the 95th percentile in our sample), a cutoff level between clean and moderately polluted air according to the EPA, the probability of an accident is 0.000291. The corresponding expected average loss to the government from an accident is 1,073 NIS; thus, the maximum amount of subsidy would be the same value. By contrast, for a level of 100 ppb (approximately the 99th percentile in our sample), a cutoff level between moderate and unhealthy pollution levels according to the EPA, the probability of an accident is 0.000507, and the maximum amount of subsidy is 1,868 NIS.

These findings suggest that for most pollution levels, given the costs, this policy is not cost-efficient for dealing with construction site accidents associated with increased air pollution. However, for very high pollution levels, especially considering that the welfare costs of an accident calculated in this paper are an underestimation, this policy might be relevant for construction sites on the low end of potential losses from temporary closures. This suggests that perhaps more focus should be given to other potential mitigation channels such as targeted interventions based on data-driven predictions on construction sites

[31]A report by an appraiser office finds an estimated average loss of 9,000 NIS for a relatively large construction site being closed for a period of 24 hours. https://www.ynet.co.il/articles/0,7340,L-5428318,00.html accessed July 19th, 2022.

[32] We also add the 95 percent lower and upper bounds, calculated using bootstrap confidence intervals, for the probability of an accident and subsidy levels associated which each NO_2 level.

prone to accidents, raising awareness of contractors and workers, investments in safety measures, training, safety standards, scaffolding, individual pollution sensors, and other relevant equipment.

9. Conclusion

In this study, we focused on the detrimental effects of one of the major air pollutants, nitrogen dioxide, on construction site accidents, an important factor in productivity related to the labor market. We found a strong connection between a rise in levels of NO_2 in the vicinity of the construction site and an increased probability of an accident, especially at high levels of pollution. We supported our causal estimation with a set of instrumental variable analyses and robustness checks. We do not find similar effects for particulate matter or for high temperature levels after properly controlling for omitted variables.

We also presented evidence suggestive of a mechanism where the effects of pollution are exacerbated in conditions when the worker's physiological state is challenged, such as high cognitive strain or fatigue. Our findings that strenuous work conditions aggravate the effects of pollution may have implications beyond construction site accidents. Further research should explore the importance of exposure to pollution in other high-stakes settings, such as those of first responders, physicians, and other demanding professions. Finally, we provide an example of potential policy implementation of our findings by demonstrating a cost–benefit analysis that calculates, using our estimates, the thresholds of air pollution for which it can be beneficial for the government to subsidize the closure of construction sites when pollution levels in their vicinity go above them.

References

Aguilar-Gomez, Sandra, Holt Dwyer, Joshua S. Graff Zivin, and Matthew J. Neidell (2022). This is air: The "non-health" effects of air pollution. *NBER Working Paper*, 29848.

Aragon, Fernando M., Juan Jose Miranda, and Paulina Oliva (2017). Particulate matter and labor supply: The role of caregiving and non-linearities. *Journal of Environmental Economics and Management*, 86, 295–309.

Arceo, Eva, Rema Hanna, and Paulina Oliva, (2016). Does the effect of pollution on infant mortality differ between developing and developed countries? Evidence from Mexico City. *Economic Journal*, 126(591), 257–280.

Benmarhnia, Tarik, Prashant Bharadwaj, and Mauricio Romero. Using Instrumental Variables for Assessing the Effects of Air Pollution on Health: A Cautionary Tale.

Brook, Robert D., and Sanjay Rajagopalan (2007). Air pollution and cardiovascular events. *The New England journal of medicine,* 356(20), 2104-2106.

Burkhardt, Jesse, Jude Bayham, Ander Wilson, Ellison Carter, Jesse Berman, Katelyn O'Dell, Bonne Ford, Emily V. Fischer, and Jeffrey R. Pierce (2019). The effect of pollution on crime: Evidence from data on particulate matter and ozone. *Journal of Environmental Economics and Management*, 98, 102267.

Chambers, Matthew L. Fine Particulate Air Pollution and Accident Risk: Three Essays. Diss. Vanderbilt University, 2021.

Chang, Tom, Joshua Graff Zivin, Tal Gross, and Matthew Neidell (2016). Particulate pollution and the productivity of pear packers. *American Economic Journal: Economic Policy*, 8(3), 141-69.

Conley, Timothy G (1999). GMM estimation with cross sectional dependence. *Journal of econometrics*, 92(1), 1-45.

Crawford, A. (2021, September 20). The global housing market is broken and it's dividing entire countries. *Bloomberg: Middle East Edition*. https://www.bloomberg.com/news/features/2021-09-19/global-housing-markets-are-hurting-and-it-s-getting-political

Delgado-Saborit, Juana Maria, Valentina Guercio, Alison M. Gowers, Gavin Shaddick, Nick C. Fox, and Seth Love (2021). A critical review of the epidemiological evidence of effects of air pollution on dementia, cognitive function, and cognitive decline in adult population. *Science of the Total Environment*, 757, 143734.

Dragomir, Carmelia Mariana, Daniel-Eduard Constantin, Mirela Voiculescu, Lucian Puiu Georgescu, Alexis Merlaud, and Michel Van Roozendael (2015). Modeling results of atmospheric dispersion of NO2 in an urban area using METI–LIS and comparison with coincident mobile DOAS measurements. *Atmospheric Pollution Research*, 6(3), 503-510.

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

Elsler, Dietmar, Jukka Takala, and Jouko Remes (2017). An international comparison of the cost of work-related accidents and illnesses. European Agency for Safety and Health at Work, 8.

Eurostat (2022). Accidents at Work—Statistics by Economic Activity. Accessed from https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Accidents_at_work_-_statistics_by_economic_activity, June 19th, 2022.

Forman, Henry Jay, and Caleb Ellicott Finch (2018). A critical review of assays for hazardous components of air pollution. *Free Radical Biology and Medicine*, 117, 202-217.

Fuller, Gary W., David C. Carslaw, and Hamish W. Lodge (2002). An empirical approach for the prediction of daily mean PM10 concentrations. *Atmospheric Environment*, 36(9), 1431-1441.

Gao, Qi, Long Liu, and Jeffrey S. Racine (2015). A partially linear kernel estimator for categorical data. *Econometric Reviews*, 34(6-10), 959-978.

Graff Zivin, Joshua, and Matthew Neidell (2013). Environment, health, and human capital. *Journal of Economic Literature*, 51(3), 689-730.

Hanlon, W. Walker (2018). London Fog: A Century of Pollution and Mortality, 1866-1965. *The Review of Economics and Statistics*, 1-49.

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

Hayfield, Tristen, and Jeffrey S. Racine (2008). Nonparametric econometrics: The np package. *Journal of statistical software*, 27, 1-32.

Hewitt, C. Nicholas (1991). Spatial variations in nitrogen dioxide concentrations in an urban area. Atmospheric Environment. Part B. *Urban Atmosphere*, 25(3), 429-434.

Holub, Felix, Laura Hospido, and Ulrich J. Wagner (2020). Urban air pollution and sick leaves: Evidence from social security data.

Li, Qi, and Jeff Racine (2004). Cross-validated local linear nonparametric regression. *Statistica Sinica*, 485-512.

National Safety Council, United States (2021). Save lives, from the workplace to anyplace. Accessed from https://injuryfacts.nsc.org/work/costs/work-injury-costs/, June 19th, 2022.

Negev, Maya (2020). Air Pollution Policy in Israel. *Atmosphere*, 11(10), 1065.

Poland, Michelle, Isabelle Sin, and Steven Stillman (2020). Why are there more accidents on Mondays? Economic incentives, ergonomics or externalities. *IZA Discussion Paper*, 12850.

Robinson, Peter M. (1988). Root-N-consistent semiparametric regression. *Econometrica: Journal of the Econometric Society*, 931-954.

Sager, Lutz (2019). Estimating the effect of air pollution on road safety using atmospheric temperature inversions. *Journal of Environmental Economics and Management*, 98, 102250.

Sakhvidi, Mohammad Javad Zare, Jun Yang, Emeline Lequy, Jie Chen, Kees de Hoogh, Noemie Letellier, Marion Mortamais, Anna Ozguler, Danielle Vienneau, Marie Zins, Marcel Goldberg, Claudine Berr, and Benedicte Jacquemin (2022). Outdoor air pollution exposure and cognitive performance: findings from the enrolment phase of the CONSTANCES cohort. *The Lancet Planetary Health*, 6(3), e219-e229.

Salehi Sichani, Mahdi, SangHyun Lee, and Aminah Robinson Fayek (2011). Understanding construction workforce absenteeism in industrial construction. *Canadian Journal of Civil Engineering*, 38(8), 849-858.

Siegel, Jenifer Z., and Molly J. Crockett (2013). How serotonin shapes moral judgment and behavior. *Annals of the New York Academy of Sciences*, 1299(1), 42-51.

Vega-Calderón, Luis, Ricardo Almendra, Pablo Fdez-Arroyabe, María T. Zarrabeitia, and Ana Santurtún (2021). Air pollution and occupational accidents in the Community of Madrid, Spain. *International Journal of Biometeorology*, 65(3), 429-436.

[US-EPA]. The United States Environmental Protection Agency. 2011. Air Quality Guide for Nitrogen Dioxide. *Office of Air and Radiation* (6301A). EPA-456/F-11-003. Accessed from www.airnow.gov, June 19th, 2022.

[US-EPA]. The United States Environmental Protection Agency. 2018. Technical Assistance Document for the Reporting of Daily Air Quality – the Air Quality Index (AQI). *Office of Air Quality Planning and Standards*. EPA 454/B-18-007. Accessed from www.airnow.gov, June 19th, 2022.

Viehmann, Anja, Sabin Hertel, Kateryna Fuks, Lewin Eisele, Susanne Moebus, Stefan Möhlenkamp, Michael Nonnemacher, Hermann Jakobs, Raimund Erbel, Karl-Heinz Jockel, and Barbara Hoffmann (2015). Long-term residential exposure to urban air pollution, and repeated measures of systemic blood markers of inflammation and coagulation. *Occupational and environmental medicine*, 72(9), 656-663.

Wang, Chaom, Fan Zhang, Julian Wang, James K. Doyle, Peter A. Hancock, Cheuk Ming Mak, and Shichao Liu (2021). How indoor environmental quality affects occupants' cognitive functions: A systematic review. *Building and environment*, 193, 107647.

World Health Organization. (2021). WHO/ILO joint estimates of the work-related burden of disease and injury, 2000–2016: global monitoring report. *In WHO/ILO joint estimates of the work-related burden of disease and injury, 2000–2016: global monitoring report*.

Figure 1: Monitors and Active Construction Sites in Israel

Figure 2: Distribution of Construction Accidents

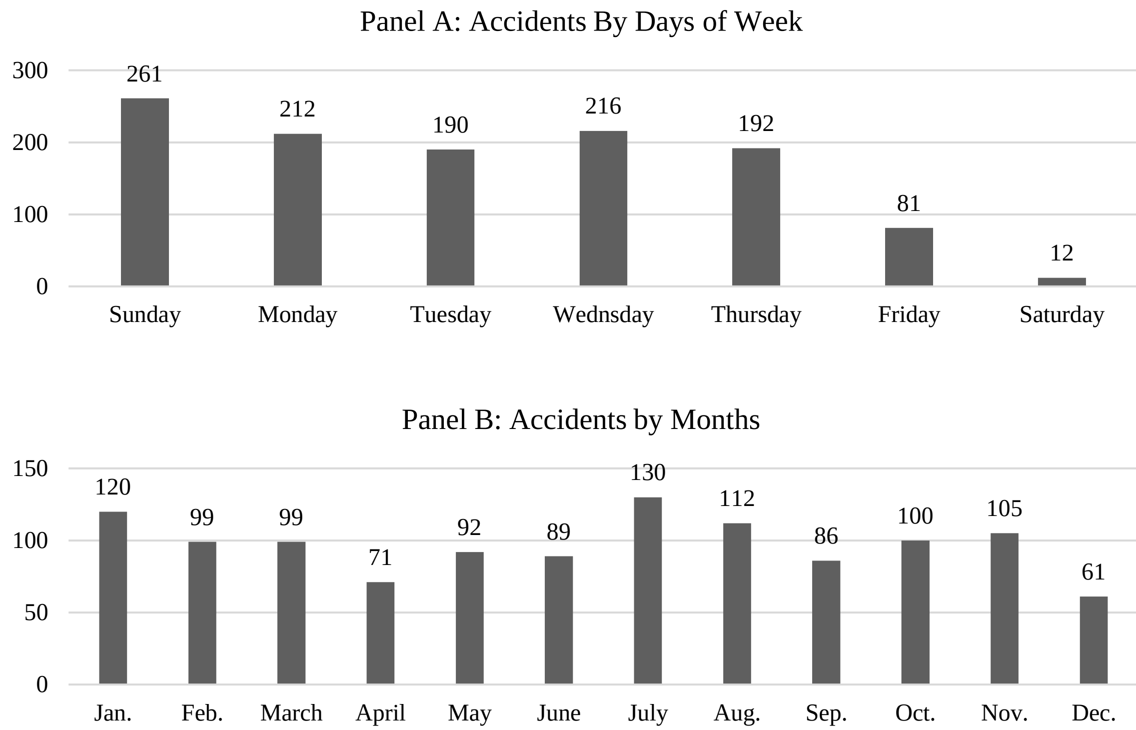
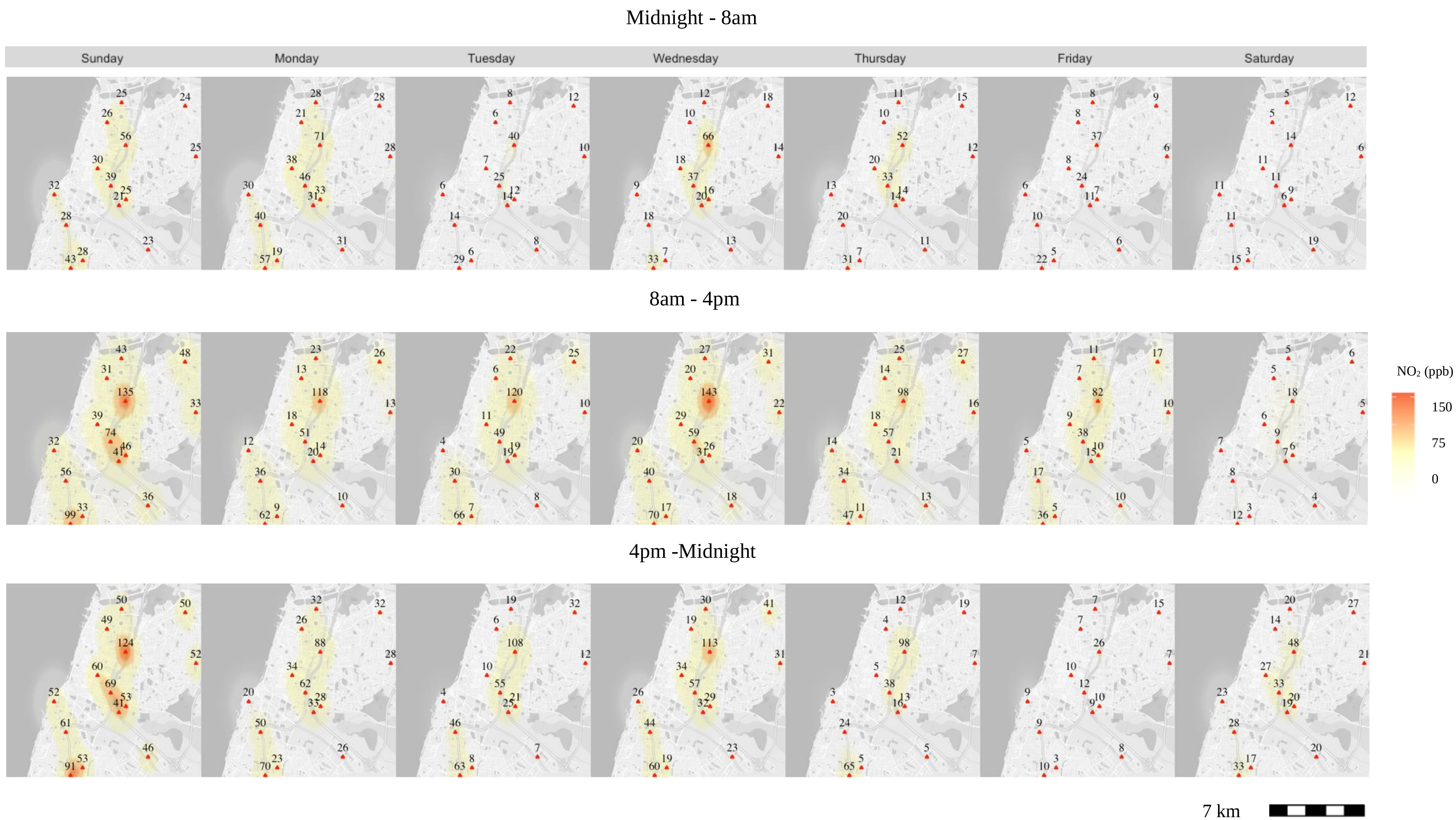


Figure 3: Nitrogen Dioxide Variation Across Time and Space



Notes: Each figure represents the amount of Nitrogen Dioxide (NO_2) measured at each of the monitoring stations (shown as triangles) in 8-hour intervals for each day of the week from January 21st to January 28th, 2018. The color shown next to each monitor is determined by the amount of NO_2 measured at each monitor (found above each triangle in the figures). The image shows an enlarged representation of Israel's Central District, using monitors from Tel-Aviv, Jaffa, Holon, and other near cities.
Map data: Google, Mapa GISrael, 2022.

Table 1: Descriptive Pollutant Statistics

Variable	Units	Hours Measured	Monitors	Obs.	Average Rate	Standard Deviation
NO	Ppb	00-08	172	131,852	11.4	41.5
		08-16	172	130,714	16.9	83.5
		16-24	170	131,571	14.1	68.0
NO_2	Ppb	00-08	172	136,492	10.9	9.9
		08-16	172	134,707	10.1	18.0
		16-24	170	136,697	12.4	14.9
Temperature	Celsius	00-08	125	111,176	18.9	6.0
		08-16	125	111,156	24.7	6.4
		16-24	125	111,649	21.5	6.2
Wind	m/sec	00-08	114	101,905	1.8	1.3
		08-16	114	101,981	3.3	1.4
		16-24	114	102,253	2.3	1.2
Humidity	%	00-08	111	88,684	72.4	18.5
		08-16	111	91,280	52.6	15.8
		16-24	111	91,362	66.2	17.4
$PM_{2.5}$	µg/m3	00-08	102	65,170	20.8	12.5
		08-16	102	64,317	21.3	14.8
		16-24	100	65,343	20.6	16.0
SO_2	Ppb	00-08	100	86,180	0.8	0.9
		08-16	100	85,921	1.2	1.7
		16-24	100	86,641	0.9	1.1
O_3	Ppb	00-08	75	64,352	27.1	13.2
		08-16	75	63,993	45.9	10.7
		16-24	75	64,583	36.0	11.9
PM_{10}	µg/m3	00-08	31	23,285	44.3	53.6
		08-16	31	23,021	55.6	70.6
		16-24	31	23,379	48.1	54.6
CO	Ppm	00-08	21	16,709	0.4	0.5
		08-16	20	16,590	0.4	0.6
		16-24	21	16,786	0.4	0.6

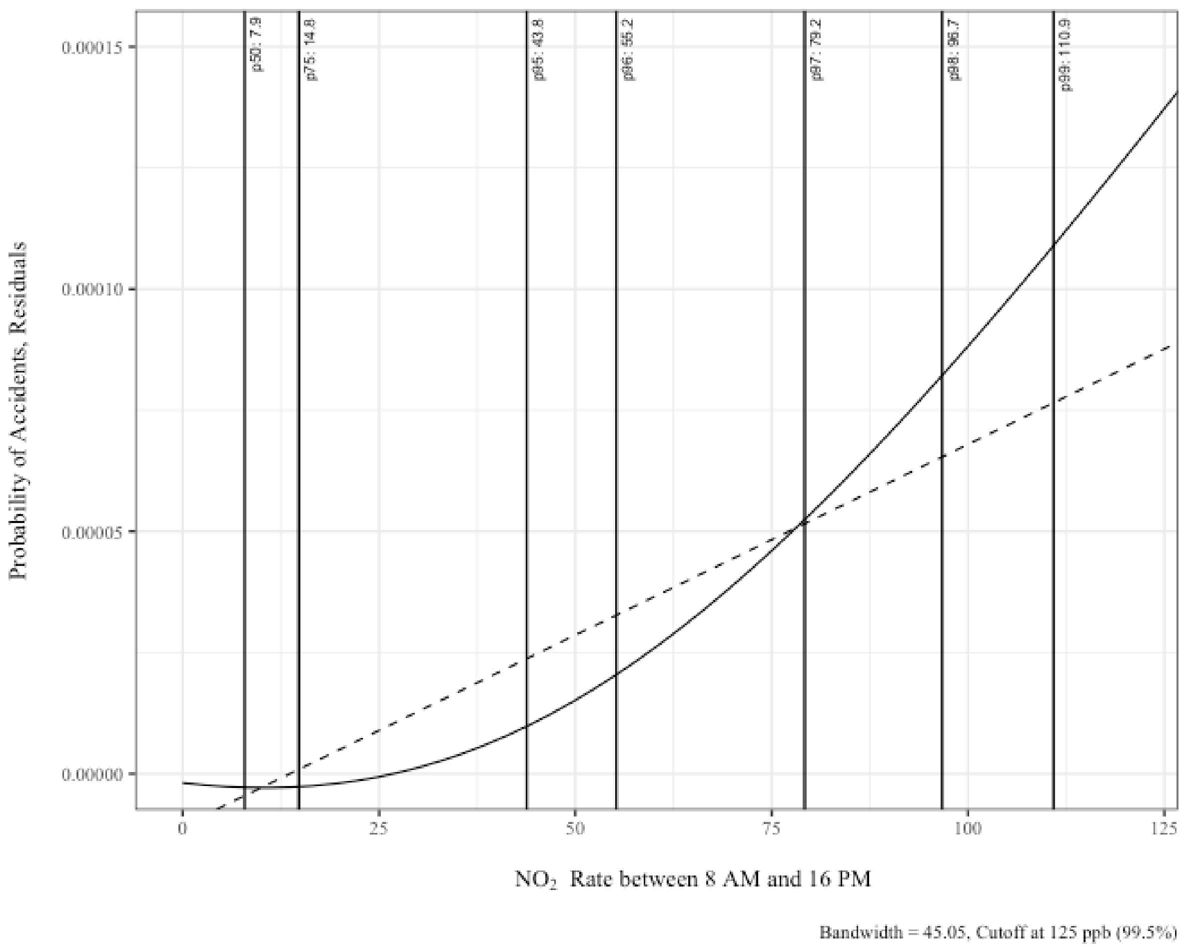
Notes: This table presents sample statistics by variables. Retrieved from Israel's Ministry of Environmental Protection between 1 January 2017 and 19 November 2019. Each observation is an 8-hour mean of 5 minutes interval measurement.

Table 2: Effect of Nitrogen Dioxide (NO_2) on the Probability of a Construction Work Accident

	OLS		Instrument: Average NO_2 Levels in 5-10 km Radius	Instrument: NO_2 Levels Between Midnight-8 AM		Nonlinear
	(1)	(2)	(3)	(4)		(5)
NO_2	0.039***	0.033***	0.037**	0.040***	99th Percentile	4.33**
	(0.011)	(0.012)	(0.017)	(0.015)		(1.715)
					95th Percentile	1.586
						(1.076)
Kliebergen-Paap Wald F-statistic			1,435.3	1,855.4		
Reduced Form			0.026**	0.031***		
			(0.012)	(0.012)		
Weather Controls		Yes	Yes	Yes		Yes
Time FE		Yes	Yes	Yes		Yes
Site FE		Yes	Yes	Yes		Yes
10 ppb Increase on Prob. of Accident	30%	25%	28%	31%	99th Percentile	377%
					95th Percentile	138%
Clusters	5,583	5,583	5,083	5,378		5,583
Observations	2,189,124	2,189,124	2,075,089	2,169,647		2,189,124

Notes: The dependent variable is the probability of an accident occurring at the construction site. The coefficient stated belongs to the independent variable, which is the rate of the pollutant between 8 a.m. and 4 p.m. and multiplied by 1,000 for ease of reading. Time-fixed effects contain the year, month, and day of the week dummy variables. Weather variables include wind, humidity percentage, temperature rate, and equivalent squared variables. For the nonlinear regression, the levels are the NO_2 AQI moderate and unhealthy for sensitive group rates, which correspond roughly to the thresholds of the 99th and 95th percentile (53 and 100 ppb, respectively). The first instrument is a simple average of the NO_2 rates in the 5-10 km radius from each construction site between 8 a.m. and 4 p.m. The second instrument is the rate between midnight and 8 AM in the closest monitor with a NO_2 reading within a 1 km from the site. Standard errors are robust, adjusted for clusters by sites, and appear in parentheses. The effect of 10 ppb is calculated compared to the average accident rate in each regression.
* p<0.1 ** p<0.05 *** p<0.01

Figure 4: Semi-Parametric Estimation of the Effect of NO_2 on the Probability of an Accident, Distance Limited to 1 km



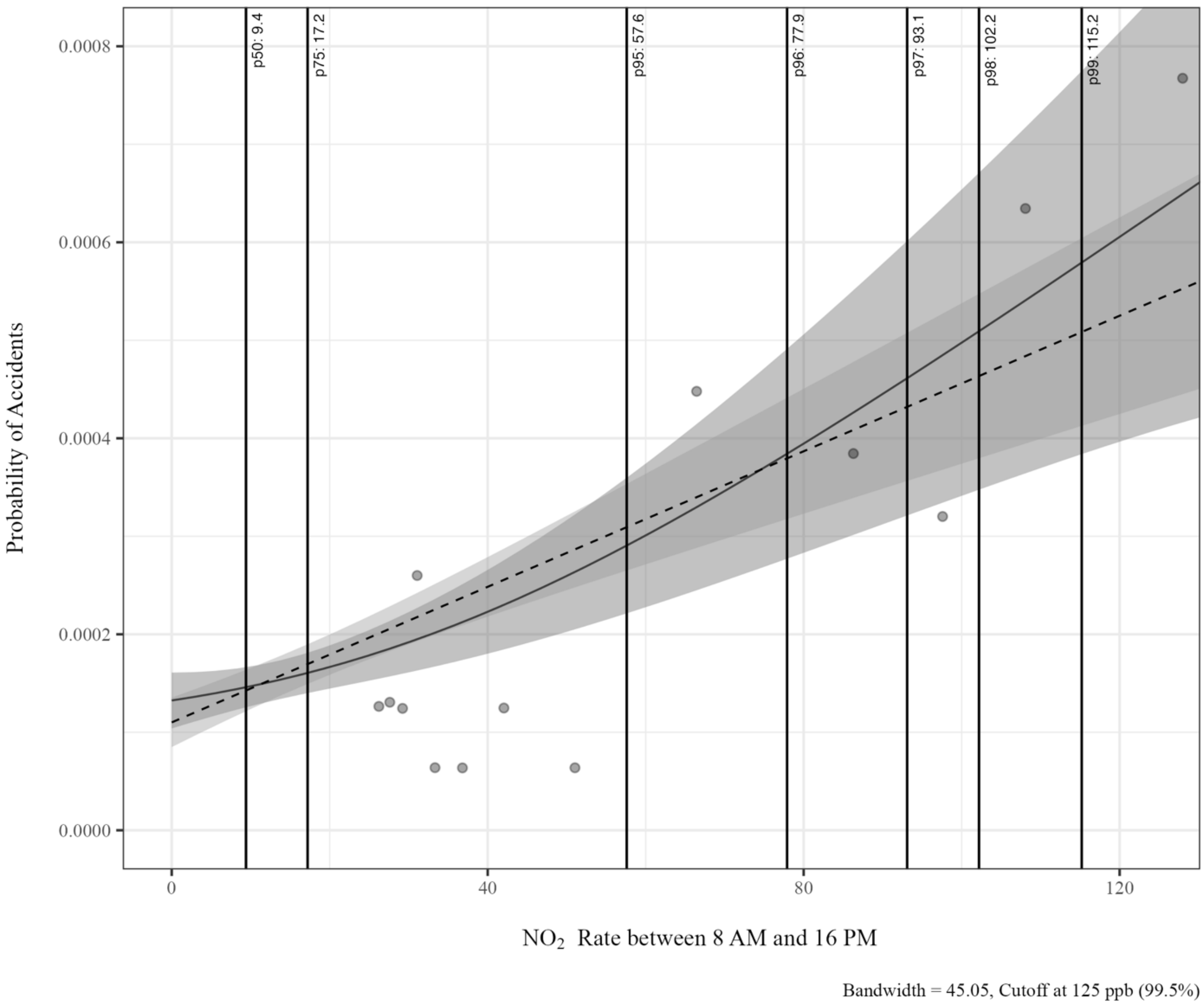
Notes: The continuous line represents the semi-parametric estimation of the connection between NO_2 levels at the closest measuring station and the probability of an accident at a construction site. The dashed line represents the liner connection.

Table 3: Robustness of the Effect of Nitrogen Dioxide (NO_2) on the Probability of a Construction Accident. Varying Monitor's Distance from Site, Limiting Wind Direction and Applying the Air Quality Index

	Monitor's Distance Robustness				Wind Direction	General AQI		
	1 km	1.5 km	2 km	5 km	180 degrees from monitor to site	Instrument: Average NO2 Rate in 5-10 km Radius	Instrument: NO2 Rate Between Midnight-8AM	Multiple Treatments
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NO_2	0.0033***	0.0018**	0.0008	0.0004	0.0039**	0.0042**	0.0041**	0.0039***
	(0.0013)	(0.0008)	(0.0006)	(0.0005)	(0.0018)	(0.0019)	(0.0020)	(0.0015)
AQI (excluding NO_2)								-0.0008
								(0.0004)
Kliebergen-Paap Wald F-statistic						1,322.8	2,398.1	
Reduced Form						0.0038**	0.0034**	
						(0.0017)	(0.0016)	
10 ppb Increase on Prob. of Accident	25%	15%	8%	4%	30%	27%	27%	30%
Clusters	5,583	10,119	12,765	18,896	5,433	4,855	5,087	5,082
Observations	2,189,124	4,119,202	5,211,326	7,803,472	1,185,624	1,210,481	1,249,192	1,243,497

Notes: The dependent variable is the probability of an accident occurring at the construction site. The coefficient stated belongs to the independent variable, which is the rate of the pollutant between 8 a.m. and 4 p.m. and multiplied by 1,000 for ease of reading. All regressions include time, weather, and site-fixed effects. Time-fixed effects contain the year, month, and day of the week dummy variables. Weather variables contain the wind, humidity, and temperature rate from relevant hours and equivalent squared variables. Column (5) restricts the sample to observations in which the wind direction is within 90 degrees to each side of the site's angle from the pollution monitor. For columns (6)-(7) the AQI index is computed with respect to the EPA standards, converting each pollutant's 8 a.m. to 4 p.m. rate to its corresponding AQI level and then taking the maximum level within all pollutants. The distance attributed to the index is the distance of the pollutant with the highest index level, and observations are restricted to 1 km for both NO_2 and the AQI. Column (8) regresses an AQI index excluding NO_2 as another treatment, where observations are restricted to a 1 km distance with respect to both treatments' distances. Standard errors are robust, adjusted for clusters by sites, and appear in parentheses. The effect of 10 ppb is calculated compared to the average accident rate in each regression.
* p<0.1 ** p<0.05 *** p<0.001

Figure 5: Nonparametric Estimation of the Effect of NO_2 on the Probability of an Accident, Excluding Weekends and Distance Limited to 1 km



Notes: The continuous line represents the non-parametric estimation of the connection between NO_2 levels at the closest measuring station and the probability of an accident at a construction site. The dashed line represents the liner connection. The gray dots represent the average probability of an accident for the group of observations within the same percentile of Nitrogen Dioxide levels, above the 85th Percentile. The dark shaded area represents the 95 percent confidence intervals based on the robust and clustered standard errors which relate to the linear model, while the light gray area represents the 95 percent bootstrap confidence intervals related to the non-parametric estimation.

Table 4: Supporting Evidence on the Possible Mechanism for the Effect of Nitrogen Dioxide (NO_2) On Construction Accidents

	Baseline	Wind		Temperature		Humidity			Day of the Week
		Above 75th Percentile (3.7 m/s)	Below 75th Percentile (3.7 m/s)	Above 75th Percentile (29.9 Celsius)	Below 75th Percentile (29.9 Celsius)	Above 75th Percentile (62.2%)	Below 75th Percentile (62.2%)		Interaction With Nitrogen Dioxide Levels (Sunday x NO2 is the Omitted Level)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)		(8)
NO_2	0.0033***	0.0069***	0.0023*	0.0047**	0.0025**	0.0052	0.0031**	NO_2	0.0083**
	(0.0013)	(0.0012)	(0.0012)	(0.0022)	(0.0011)	(0.0035)	(0.0012)		(0.0035)
								Mon. × NO_2	-0.0056
									(0.0039)
								Tue. × NO_2	-0.0067*
									(0.0034)
								Wed. × NO_2	-0.0060**
									(0.0027)
								Thu. × NO_2	-0.0068*
									(0.0036)
10 ppb Increase on Prob. of Accident	25%	56.9%	19.1%	34.0%	18.0%	53.8%	32.0%		
Clusters	5,583	5,317	5,317	5,054	5,055	5,226	5,227		5,583
Observations	2,189,124	574,489	1,555,964	514,341	1,651,522	531,262	1,653,066		2,189,124

Notes: The dependent variable is the probability of an accident occurring at the construction site. The coefficient stated belongs to the independent variable, which is the rate of the pollutant between 8 a.m. and 4 p.m. multiplied by 1,000 for ease of reading. All regressions include time, weather, and site-fixed effects. Time-fixed effects contain the year, month, and day of the week dummy variables. Weather variables contain the wind, humidity, and temperature rate from relevant hours and equivalent squared variables. Column (8) includes the interaction terms between the day of the week and Nitrogen Dioxide levels to the baseline linear model with controls presented in equation (1). The omitted level is the interaction between Nitrogen Dioxide levels and a dummy variable for observations occurring on Sunday. Standard errors are robust, adjusted for clusters by sites, and appear in parentheses. The effect of 10 ppb is calculated compared to the average accident rate in each regression.

* $p<0.1$ ** $p<0.05$ *** $p<0.001$

Table 5: Cost Benefit Analysis of Pollution Levels and Subsidy Amount

Nitrogen Dioxide Level	Percentile	Probability of an Accident	Subsidy (NIS)	95% Confidence Intervals	
5.4	25%	0.000140	515	431	599
9.4	50%	0.000144	530	453	608
17.2	75%	0.000159	586	511	660
30.2	91%	0.000193	709	595	823
32.1	92%	0.000201	739	613	864
34.8	93%	0.000209	770	632	907
39.0	94%	0.000218	803	652	953
45.6	95%	0.000247	910	718	1,102
57.6	96%	0.000291	1,073	817	1,329
77.9	97%	0.000394	1,449	1,040	1,858
93.1	98%	0.000464	1,707	1,188	2,227
102.2	99%	0.000507	1,868	1,276	2,459
115.2	100%	0.000582	2,141	1,417	2,864

Notes: This table presents a calculation of the maximum subsidy amount the government can pay a contractor for the closure of the construction site for the day, to offset expected injury insurance payments, conditional on local levels of Nitrogen dioxide. The expected lifetime accident payout by the government is 3.681 million NIS, and the subsidy amount is calculated by multiplying this amount by the probability of an accident corresponding to every Nitrogen dioxide level according to our nonparametric estimate; see paper for details. The 95% confidence intervals are calculated using a Bootstrap estimation method.

Online Appendix

Table A1: Effect of Sites' Closest Rate of Nitrogen Dioxide Rate, within 1 km on the Average in the 5-10 km Radius, by Company Size

	Big Company	Small Company	Interaction
	(1)	(2)	(3)
NO_2	0.190***	0.246***	0.237***
	(0.011)	(0.008)	(0.007)
NO_2 x Big Company			-0.016
			(0.012)
Weather Controls	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Site FE	Yes	Yes	Yes
Clusters	990	4,284	5,274
Observations	417,941	1,657,339	2,075,280

Notes: The dependent variable is the closest reading of Nitrogen Dioxide in ppb between 8 a.m. and 4 p.m. within a 1 km radius from the given construction site. The coefficient stated belongs to the independent variable which is the average of Nitrogen Dioxide between 8 a.m. and 4 p.m. within the 5-10 km radius of the site. In order to define a company's size, we used company names that were included in the data. All those that their names included the "Ltd." term were considered big and those without a name we assumed to be small. All regressions include time, weather, and site fixed effects. Time-fixed effects contain the year, month, and day of the week dummy variables. Weather variables contain the wind, humidity, and temperature rate from relevant hours and equivalent squared variables. Standard errors are robust, adjusted for clusters by sites, and appear in parentheses.
* p<0.1 ** p<0.05 *** p<0.001

Table A2: The Effect of Nitric Oxide (NO) on the Probability of a Construction Accident

			Instrument: Average Rate in 5-10 km Radius	Instrument: Rate Between Midnight-8AM		Nonlinear
	(1)	(2)	(3)	(4)		(5)
NO	0.00050***	0.00039**	0.00056*	0.00032*	99^{th} Percentile	0.347**
	(0.0002)	(0.0002)	(0.0003)	(0.0002)		(0.143)
					95^{th} Percentile	0.0524
						(0.058)
Reduced Form			0.00045*	0.00049*		
			(0.0003)	(0.0003)		
Weather Controls		Yes	Yes	Yes		Yes
Time FE		Yes	Yes	Yes		Yes
Site FE		Yes	Yes	Yes		Yes
10 ppb Increase on Prob. of Accident	4%	3%	4%	2%	99^{th} Percentile	302%
					95^{th} Percentile	46%
Clusters	5,577	5,577	5,268	5,577		5,577
Observations	2,175,535	2,175,535	2,062,225	2,149,505		2,175,535

Notes: The dependent variable is the probability of an accident occurring at the construction site. The coefficient stated belongs to the independent variable, which is the rate of the pollutant between 8 AM and 4 PM and multiplied by 1,000 for ease of reading. Time-fixed effects contain the year, month, and day of the week dummy variables. Weather variables include the wind, humidity percentage, temperature rate and the equivalent squared variables. For the nonlinear regression, the levels are the NO AQI moderate and unhealthy for sensitive group rates, which correspond roughly to the 99th and 95th percentile thresholds. The first instrument is a simple average of the NO rates in the 5-10 km radius from each construction site between 8 AM and 4 PM. The second instrument is the rate between midnight and 8 AM in the closest monitor with a NO reading within 1 km from the site. Standard errors are robust, adjusted for clusters by sites, and appear in parentheses. The effect of 10 ppb is calculated compared to the average accident rate in each regression.
* p<0.1 ** p<0.05 *** p<0.01

Table A3: Testing Robustness due to Possible Spatial Auto-Correlation and Correcting for Multiple Hypothesis Testing

			Instrument: Average Rate in 5-10 km Radius	Instrument: Rate Between Midnight - 8 AM		Nonlinear
	(1)	(2)	(3)	(4)		(5)
NO_2	0.0039	0.0033	0.0037	0.0040	99th Percentile	0.433
Clustered by Site	(0.0011)***	(0.0013)***	(0.0017)**	(0.0015)***		(0.172)**
Clustered by Monitor	[0.0004]***	[0.0010]***	[0.0016]**	[0.0013]***		[0.045]***
Conley (0.69 km)	{0.0014}***	{0.0017}**	{0.0017}**	{0.0015}***		{0.208}**
					95th Percentile	0.159
						(0.108)
						[0.051]***
						{0.089}*
					99th Percentile	
p-value	0.00	0.00	0.03	0.00	p-value	0.01
Sharpened q-value	0.00	0.01	0.06	0.01	Sharpened q-value	0.02
					95th Percentile	
					p-value	0.14
					Sharpened q-value	0.21
Weather Controls		Yes	Yes	Yes		Yes
Time FE		Yes	Yes	Yes		Yes
Site FE		Yes	Yes	Yes		Yes
Clusters	5,583	5,583	5,274	5,583		5,583
Observations	2,189,124	2,189,124	2,189,124	2,189,124		2,189,124

Notes: The dependent variable is the probability of an accident occurring at the construction site. The coefficient stated belongs to the independent variable, which is the rate of the pollutant between 8 a.m. and 4 p.m. and multiplied by 1,000 for ease of reading. Time-fixed effects contain the year, month, and day of the week dummy variables. Weather variables include wind, humidity percentage, temperature rate, and equivalent squared variables. For the nonlinear regression, the levels are the NO2 AQI moderate and unhealthy for sensitive group rates, which correspond roughly to the thresholds of the 99th and 95th percentile (53 and 100 ppb, respectively). The first instrument is a simple average of the NO2 rates in the 5-10 km radius from each construction site between 8 a.m. and 4 p.m. The second instrument is the rate between midnight and 8 AM in the closest monitor with a NO2 reading within a 1 km from the site. Standard errors are robust, adjusted for clusters by sites and appear in round parentheses, adjusted for clusters by monitors appear in squared parentheses, and Conley (1999, 2008) standard errors which account for spatial correlation appear in curly parentheses. The q-value is the sharpened False Discovery Rate (FDR) corrected for multiple hypotheses testing the effect of Fine Particulate Matter ($PM_{2.5}$).
* p<0.1 ** p<0.05 *** p<0.01

Table A4: Effect of Fine Particulate Matter ($PM_{2.5}$) and Nitrogen Dioxide (NO_2) on the Probability of a Construction Accident

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$PM_{2.5}$	0.0037***	0.0037***	0.0032**	0.0029*	0.0028*	0.0028*	0.0033*	0.0007
	(0.0014)	(0.0014)	(0.0014)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0011)
NO_2	0.0039***	0.0040***	0.0035***	0.0033**	0.0032**	0.0033**	0.0042***	0.0035***
	(0.0012)	(0.0012)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0014)	(0.0013)
Year FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of the Week			Yes	Yes	Yes	Yes	Yes	Yes
Temperature				Yes	Yes	Yes	Yes	Yes
Humidity					Yes	Yes	Yes	Yes
Wind						Yes	Yes	Yes
City FE							Yes	
Site FE								Yes
Clusters	3,656	3,656	3,656	3,656	3,656	3,656	3,656	3,656
Observations	1,301,276	1,301,276	1,301,276	1,301,276	1,301,276	1,301,276	1,301,276	1,301,276

Notes: The dependent variable is the probability of an accident occurring at the construction site. The coefficient stated belongs to the independent variable, which is in the first row the rate of Fine Particulate Matter in µg/m3 units between 8 a.m. and 4 p.m., in the second row, it is the rate of Nitrogen Dioxide between the same hours in ppb units. Each row is a separate regression. All coefficients are multiplied by 1,000 for ease of reading. Weather fixed effects, such as temperature, humidity, and wind, include a squared variable with their equivalent rate and a linear variable. Standard errors are robust, adjusted for clusters by sites, and appear in parentheses.
* $p<0.1$ ** $p<0.05$ *** $p<0.001$

Table A5: Effect of Temperature on the Probability of a Construction Accident

	(1)	(2)	(3)	(4)	(5)	(6)
Temp (35-40)	0.183*	0.160	0.163	0.163	0.085	0.037
	(0.101)	(0.110)	(0.110)	(0.110)	(0.104)	(0.102)
Temp (30-35)	0.136***	0.113**	0.111**	0.094*	0.041	0.011
	(0.050)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)
Temp (25-30)	0.061	0.041	0.039	0.031	-0.006	-0.020
	(0.040)	(0.042)	(0.043)	(0.043)	(0.042)	(0.043)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Humidity		Yes	Yes	Yes	Yes	Yes
Wind			Yes	Yes	Yes	Yes
Day of the Week FE				Yes	Yes	Yes
City FE					Yes	
Site FE						Yes
Clusters	4,890	4,890	4,890	4,890	4,890	4,890
Observations	1,838,439	1,838,439	1,838,439	1,838,439	1,838,439	1,838,439

Notes: The dependent variable is the probability of an accident occurring at the construction site. The coefficient stated belongs to the independent variable, which is the temperature between 8 a.m. and 4 p.m. in degrees Celsius and is multiplied by 1,000 for ease of reading. Weather variables contain the wind, humidity, and temperature rate from relevant hours and equivalent squared variables. The omitted level is the bin between 20-25 degrees Celsius. Lower bins in 5 degrees Celsius intervals and a bin for 40 degrees and over are included in all regressions but are not shown. Standard errors are robust, adjusted for clusters by sites, and appear in parentheses.
* p<0.1 ** p<0.05 *** p<0.001