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ABSTRACT

Air pollution can adversely affect physiological and cognitive performance. This study estimates the causal effect of increased nitrogen dioxide (NO2), a primary air pollutant, on construction work accidents, a significant factor related to labor market productivity losses. Using data from all construction sites and pollution monitoring stations in Israel, we find a strong and significant effect on accidents, with a 377% (138%) increase on high (moderate) NO2 pollution days compared to clean air levels. Our mechanism analysis suggests the effect is exacerbated under cognitive strain or worker fatigue. A cost-benefit analysis, supported by a nonparametric estimation, examines subsidizing site closures 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 et al. 2022 for a recent survey).

We contribute to this literature by investigating the effects of air pollution on work accidents, which are significant yet understudied factors affecting productivity in the labor market. Work-related accidents, with construction workers at particular risk, cause an estimated 360,000 deaths worldwide each year and 26.5 million disability-adjusted life years (World Health Organization, 2021). These outcomes also translate to significant productivity losses; according to the National Safety Council, United States (2021) 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 2017, the costs of work-related accidents and illnesses accounted for around 3.3 percent of GDP (Elsler et al., 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 non-linear 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 95^{th} and 99^{th} percentiles in our sample. At these levels, the likelihood of an accident is increased by 138 and 377 percent, respectively, compared to levels of clean air (below 55 ppb, the 95^{th} percentile).

We support the causal identification by including construction site and time-fixed

[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.

effects in the regressions while also controlling for other factors potentially associated with work accidents, such as wind, humidity, and temperature. 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 pollution measurements 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 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 the night before, should only affect the probability

[4] We also use data on wind direction to limit our sample to days 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 simultaneously.

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 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 endogeneity issues. We demonstrate that the effects of particulate matter and high temperature, which have been linked to increased probability of accidents in previous studies that looked at larger geographical units, do not persist when controlling for construction site fixed effects. In contrast, 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

[5]We also show suggestive evidence that the effect of NO_2 is not driven by its potential codetermination with other pollutants. And that the differential effect compared to $PM_{2.5}$ and temperature is not due to lack of residual variation.

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 each contractor to shut down their daily operations. 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 workers 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 2, we present a review of the relevant literature and the contribution of our study. Section 3 presents institutional information in the context of Israel and our data. Section 4 presents our empirical strategy. In Section 5, we present our empirical results. Section 6 presents our robustness checks. Section 7 discusses potential mechanisms and present results related to other potential determinants of construction accidents. Section 8 presents our cost-benefit analysis, and Section 9 concludes.

2 Related Literature

Physicians and epidemiologists have mainly examined the direct health effects of air pollution on health outcomes. They found 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, 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, 2013; Chang et al., 2016), reduces labor supply (Aragon et al., 2017; Hanna and Oliva, 2015; Holub et al., 2020), and has adverse effects on human capital formation (Ebenstein et al., 2016).

Our paper contributes to the existing literature by examining the effects of air pollution on a less studied but significant factor affecting labor outcomes: workplace accidents. Specifically, we focus on a less explored, ubiquitous air pollutantnitrogen dioxide. The paper most closely related to ours is Vega-Calderón et al. (2021), which found a connection between increased levels of PM_{10} and NO_2 and workplace accidents in Madrid, Spain. Our study takes a more detailed approach, leveraging highly granular data, allowing for a more precise estimation. We also incorporate controls for humidity levels, site-fixed effects, a nonparametric estimation, and an instrumental variable analysis. As a result, these improvements allow us to interpret our findings causally.

Furthermore, our paper examines potential mechanisms and conducts a cost-benefit analysis of a potential welfare-improving policy. Notably, we find significantly stronger effects of air pollution. This heightened impact may be attributed to the accuracy of pollution level measurements at construction sites facilitated by the extensive network of monitoring stations near the construction sites in our data. The improved accuracy minimizes the risk 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 and 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 additional construction site accidents.

3.1 Construction Sites and Accidents Data

The initial construction site sample the Ministry of Economy and Industry provided 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 sites 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 that the Ministry of Economy and Industry provided included 1,316 accidents during the sample period. The accidents provided by Kav LaOved did

[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.

not include site IDs matching the ministry's data. We matched the accidents to the sites by their address instead, which resulted in an additional 31 accidents. Merging the dataset of the sites 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 Israels 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 Israels construction sector was around 272,500 during the sample period, the yearly accident rate resulted in 161 accidents per 100k workers.[10]

3.2 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 (celsius), humidity (%), as well as other pollutants at 173 monitoring stations throughout Israel for the sample period. The monitoring station locations 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

[8]Accidents reported by the Ministry of Economy and Industry are those reported under Israels 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 the US and the EU for the same time period was 1,103 and 3,270 per 100k workers, respectively (Eurostat, 2022; Centers for Disease Control and Prevention, 2020). There is no indication that this underreporting is related to pollution levels and could only potentially reduce the statistical power of our analysis.

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 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.

Table 1 shows summary statistics for pollution and weather variables in our dataset, while Online Appendix Table A1 presents the correlation matrix related to those variables. In 2017, the European Environmental Agency reported an annual mean average of 22.0 $\mu g/m^3$ for NO_2 across the European Union states,[12] while the yearly average in the US was 15.5 $\mu g/m^3$, according to data from the EPA. Converting our data from ppb units to $\mu g/m^3$ at 25 degrees Celsius and 1 atm (standard atmospheric pressure) results in a mean of 20.9 $\mu g/m^3$ 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]

[11]See the section 6 for a supporting analysis including other pollutants.

[12]Data is from a 2019 report by the European Environmental Agency (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) $\mu g/m^3$ averages (Negev, 2020).

4 Econometric Strategy - Identification

4.1 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[14]:

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

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 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

[14] We use a linear probability model instead of a nonlinear maximum likelihood model such as Probit, Logit, or Poisson. We make this choice because construction site accidents are rare in our sample, with many sites not having any accidents. A nonlinear maximum likelihood estimation would exclude all construction sites where no accidents occurred during our study period, resulting in an endogenous sample. When including site fixed effect into the nonlinear maximum likelihood model, all variables within site variation are equal to zero. (for an in-depth discussion, see Autor et al. (2014))

selection issues by adding construction site fixed effects to our estimation equation. This allows us to focus on variations within the construction site 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).[15]

Another potential issue in the literature evaluating air pollution impacts is 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 et al., 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.[16] Avoidance behavior is even less likely to occur in any asymmetric way related to proneness to accidents.[17]

[15] We also examine specifications where we add the week of the year or day of the year as temporal fixed effects. Our results are robust to the addition of these additional controls.

[16] 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.

[17] See also Salehi Sichani et al. (2011), who find no correlation between tenure at work and absenteeism in the industrial construction workforce.

4.2 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 et al., 2002). To further support this claim, we use a construction companys limited liability status, a proxy for construction site size, and find no evidence that large-sized construction sites affect pollution in this range.[18] We also assume that pollution levels measured at more distant 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:

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

[18] In Online Appendix Table A2, 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 construction sites and then for the sample of bigger construction sites. We find that these estimates are not statistically significantly different from each other.

$$NO_{2st} = \alpha + \delta NO_{2,g(5-10km)st} + f(Temp_{st}, Wind_{st}, Hum_{st}) + S_s + DMY_t + v_{st} \quad (3)$$

Second stage:

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

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 ($NO_{2,st-0.5}$) 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 ($NO_{2,g(5-10km)st}$). $Pred(NO_{2,st})$ are the values of NO_2 predicted in the first-stage equations 2 and 3.

4.3 Non-linear 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 be due to the lack of ability to measure subclinical health effects of exposure to lower pollution levels or due to the potential non-linear impact of pollution. The economic literature has focused less on non-linear effects when examining the effects of air pollution.[19] In this section, we investigate whether there are non-linearities 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 95th 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 99th percentile

[19]See Arceo et al. (2016) and Hanlon (2018) for some notable exceptions.

in our sample.[20] Formally,

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

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

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

where $H(NO_{2,st})$ is a local linear 2^{nd} 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

[20] The United States Environmental Protection Agencys (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+.

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.[21] The first stage for both instruments is strong, with an F-statistic of 1,435 and 1,855, respectively.[22] 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 non-linear 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 95^{th} and 99^{th} percentile and above the 99^{th} percentile of NO_2 levels, respectively), as specified in equation 5. The results suggest that we have a non-linear 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

[21] The results are robust to using different cutoffs of the radius.

[22] 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. We further test for the exogeneity of our instruments using the Sargen-Hansen overidentification tests. The tests do not reject the null hypothesis that the overidentifying restrictions are valid, providing suggestive evidence that the instruments are exogenous.

0.000159 percentage points (SE=0.0001076) in the probability of an accident, which translates to an increase of 138 percent. Still, it is not statistically significant at conventional levels. In comparison, a shift from clean air to high pollution levels 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 4.06 more accidents per 100,000 workers yearly, statistically significant at a 5 percent level.

In Figure 4, we present the results of our semiparametric specification described in equation 6. We observe a convex non-linear 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 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), 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.[23]

6 Robustness

In this section, we report a set of robustness tests to validate further 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 where 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, and 5 km 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

[23]The results are consistent and remain significant when we use NO instead of NO_2 as our measure of pollution and are presented in Online Appendix Table A3. 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 NO_x (US-EPA, 2011).

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 et al., 2023; Aguilar-Gomez et al., 2022). We believe this issue is less of a concern in our 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. Compared to a general instrument, this would decrease likelihood of under-identification, which could affect accidents through different pollutants. To further support the case against this under-identification, we compute a general air quality index (AQI). This commonly used overall index measure includes NO_2 and the other five 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, we find similar results when we instrument for the general AQI compared to instrumenting for NO_2. In that case, we 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 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 winds direction can determine 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 simultaneously. In column (5) of Table 3, we report the results of this specific exercise and compare them to our main specification. The results remain robust in size and significance.[24]

[24]The results remain unchanged when we use specifications with different ranges of wind direction

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 for NO_2 remains strong and significant, while the coefficient for the general AQI is close to zero. In Online Appendix Table A4, we further show that when combining NO_2 and $PM_{2.5}$ in a single "horse-race" regression and when combining NO_2, $PM_{2.5}$, SO_2 and O_3 for the limited sample of construction sites where the measurements are available for these pollutants, we find that the coefficient for the effect of NO_2 remains very similar to our main specification and has by far the largest effect on the probability of an accident, although results are noisy due to the smaller sample size.[25] These results further support our hypothesis that exposure to NO_2 rather than other potential covariates, such as other pollutants, is driving our results.

By nature, pollution is correlated over time and space, which might lead to spatial autocorrelation of the pollution at hand. In Online Appendix Table A5, we show that our results remain robust while accommodating 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 sites location and pollution that might remain in the air over certain time intervals (Conley, 1999). Second, as construction sites are assigned to their closest monitors reading within 1 km, as a robustness check, we report the clustered standard errors at the monitoring station level for our main specifications. This allows us to take into account the actual location where the pollution was estimated. All our results remain statistically significant in both cases. Finally, we ran a placebo test, replacing our same-day pollution estimator with the pollution for the two subsequent days. We observe that the coefficient diminishes and becomes insignificant (0.000014 and 0.0000084 percentage point increase for a 10 unit increase in NO_2 when replacing same-day levels with the day-after and two days-after levels, respectively). This provides supportive evidence that there is sufficient temporal variation in pollution levels to identify the effect of same-day pollution and highlights the importance of using the high frequency of pollution measurements to capture the effects of pollution accurately.

angles. The results are not presented and are available from the authors upon request.

[25] We caution that this analysis is only suggestive as NO_2 and the other pollutants might be endogenous. We support the claim that the statistical insignificance in the model, including $PM_{2.5}$, SO_2, and O_3, stems from the smaller sample size rather than endogeneity issues by running a regression with NO_2 as the sole pollutant on the same sample. Reassuringly, we find equivalent results for the effect of NO2 but in terms of magnitude and statistical significance.

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. We use indirect evidence to infer the potential effects of these changes since workers individual information is not available in our data. Poland et al. (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 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 pollutions detrimental effect on accidents may be related to worker fatigue or lack of cognitive awareness, and 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.[26] High levels of pollution might exacerbate the effect of these already difficult conditions.

As seen in columns (2-7) of Table 4, pollution plays an increased role when wind strength, temperature level, and/or humidity level are above the 75^{th} percentile, in contrast to the mild conditions where levels are below the 75^{th} percentile.[27] These findings also highlight the transitory, short-term nature of the effect of exposure to NO_2.

In this paper, we 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

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

[27] 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 75^{th} 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.

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. Compared to other pollutants, the second advantage of NO_2 is that it introduces significant spatial variability, allowing 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)). Taking this into account, we examine the effects of these determinants in our setting while also taking advantage of the high density and spatial distribution of air pollution monitoring stations in our sample to examine both the role of spatial variation of the different determinants and the importance of potential endogeneity threats biasing results when attempting to estimate the effects of environmental variables. Considering that NO_2 is a precursor of $PM_{2.5}$, an advantage of our estimation is the high temporal frequency of our observations and our focus on short term effects, which allow us to better decern the effects of NO_2 from $PM_{2.5}$ (Deryugina et al., 2019; Lin and Cheng, 2007).[28]

In Online Appendix Tables A6 and A7, we show that when controlling for only limited specifications, 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 for temperature and $PM_{2.5}$ are drastically reduced 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.[29]

The difference in the effects we find for the different pollutants and temperature

[28]As a robustness for the potential issue of NO_2 gradually converting to $PM_{2.5}$, we also estimate an alternative specification where we include daytime $PM_{2.5}$ as a control in our main instrumental variable estimates for 2, columns (3-4). The results yield comparable significant estimates for NO_2 while no effect for $PM_{2.5}$

[29]While examining these other determinants is not the main focus of our paper, for the sake of robustness, in Online Appendix Table A5, 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.

in Online Appendix Tables A4, A6, and A7 might be partially explained by a lack of spatial variation of the residual levels for the different pollutants after controlling for the various geographical fixed effects. We attempt to address this issue in several ways. First, In Online Appendix Table A8, we present an analysis similar to Fisher et al. (2012), where we regress each pollutant and temperature on the different control variables in our main specifications and examine whether there remains sufficient residual variation in the different determinants following the gradual addition of the different controls and geographic fixed effects. We observe that for NO_2 and $PM_{2.5}$, there is a decrease in the residual variation and an increase of the R^2 when adding the construction site fixed effect and a similar increase for temperature when adding the month of the year fixed effect. There does not seem to be a differential in the reduction of the residual variation between NO_2, $PM_{2.5}$, and temperature, and the reduction appears to be even larger for NO_2. This lack of difference and the finding that there appears to be a sufficient share of observations with a reasonably large residual, even after controlling for site-fixed effects, provides supportive evidence for our findings linking NO_2 with a comparably stronger effect on the probability of an accident.

Our second analysis complements our check of sufficient residual variation by examining the appropriate geographical unit of observation sufficient to capture the potential effects of the different pollutants and temperatures. For determinants with large spatial variation, a large geographical unit of observation, such as a state or county commonly used in the literature to calculate the average level, might not be granular enough to capture the local effects and overcome measurement error, which we already showed can attenuate the effect size. In Online Appendix Table A9, we show that when the unit is large, such as the country and city levels, the effects of determinants with large spatial variation, such as nitrogen dioxide, and to a smaller degree particulate matter 2.5, are weaker, and not significant and gradually become more pronounced when the unit of observation is smaller. These findings are important as they can provide guidance when considering the unit of observation for different pollutants and highlight the importance of choosing the appropriate unit of observation for each determinant studied in general.

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 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 limiting the allowed emission levels, raising public awareness, facilitating mitigation of pollution through avoidance behavior, and improving the treatment of its negative effects are some of the potential focus areas of relevant interventions. This section focuses on policies that facilitate pollution mitigation 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 construction site closures. Then, we run a back-of-the-envelope calculation on whether it might benefit 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 workers 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, all determined based on the accident's severity.

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:

$$E[costs|NO_2] = Pr(Accident|NO_2) \times Costs_{Accident\ Insurance} \quad (7)$$

where $Pr(Accident|NO_2)$ 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[30] 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)[31] multiplied by the difference between the average life expectancy ($Age^e = 83$) and the average age of the injury[32] ($\bar{Age} = 39$). This sum is then multiplied by the percentage of accidents that are a direct cause of construction site accidents[33] ($p_{con} = 10.7$ 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:

$$Cost\ of\ Accident\ Insurance = \frac{(P_1 + (P_2 \times (Age^e - \bar{Age})) \times p_{con}}{Injuries} \quad (8)$$

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 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.[34] Finally, we

[30]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.

[31]From a report by the National Insurance Institute (accessed September 29, 2022).

[32]From a report by the Israeli Parliament Research and Information Center analyzing data from the NII and the Ministry of Economy and Industry (accessed July 17, 2022).

[33]From a report by the Israeli Parliament Research and Information Center analyzing data from the NII (accessed July 17, 2022).

[34]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 (accessed July 19th, 2022).

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 non-linearities in the connection between pollution levels and the probability of an accident, Figure 5 presents a nonparametric estimation similar to its approach to equation 6. By implementing such a strategy, we predict the probability of an accident more accurately across the different pollution levels to suggest a more precise monetary subsidy based on pollution levels. Table 5 presents 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.[35] For example, at 53-ppb (approximately the 95^{th} 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 subsidy amount would be the same value. By contrast, for a level of 100-ppb (approximately the 99^{th} 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 prone to accidents, raising awareness of contractors and workers, investments in safety measures, training, safety standards, scaffolding, individual pollution sensors, respirators, 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

[35] 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.

accident, especially at high levels of pollution. We supported our causal estimation with instrumental variable analyses and robustness checks. We do not find similar effects for particulate matter or 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 workers 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 costbenefit 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.

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Tables and Figures

Figure 1: Monitors and Active Construction Sites in Israel

Figure 2: Distribution of Construction Accidents

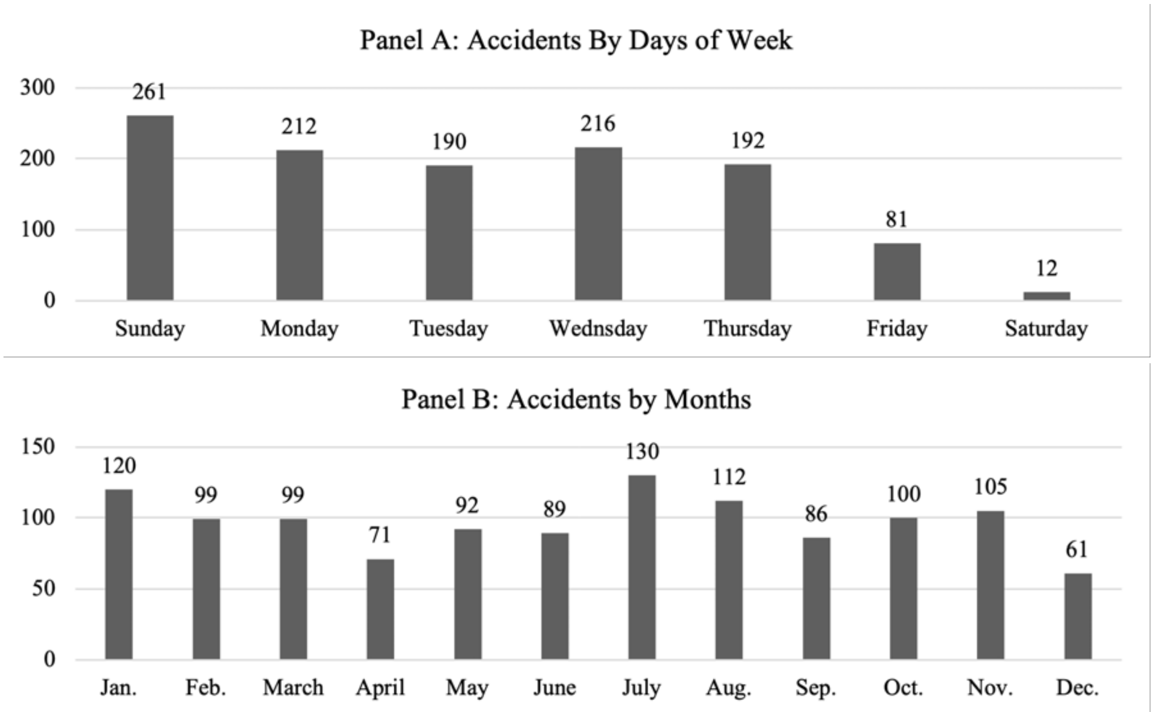
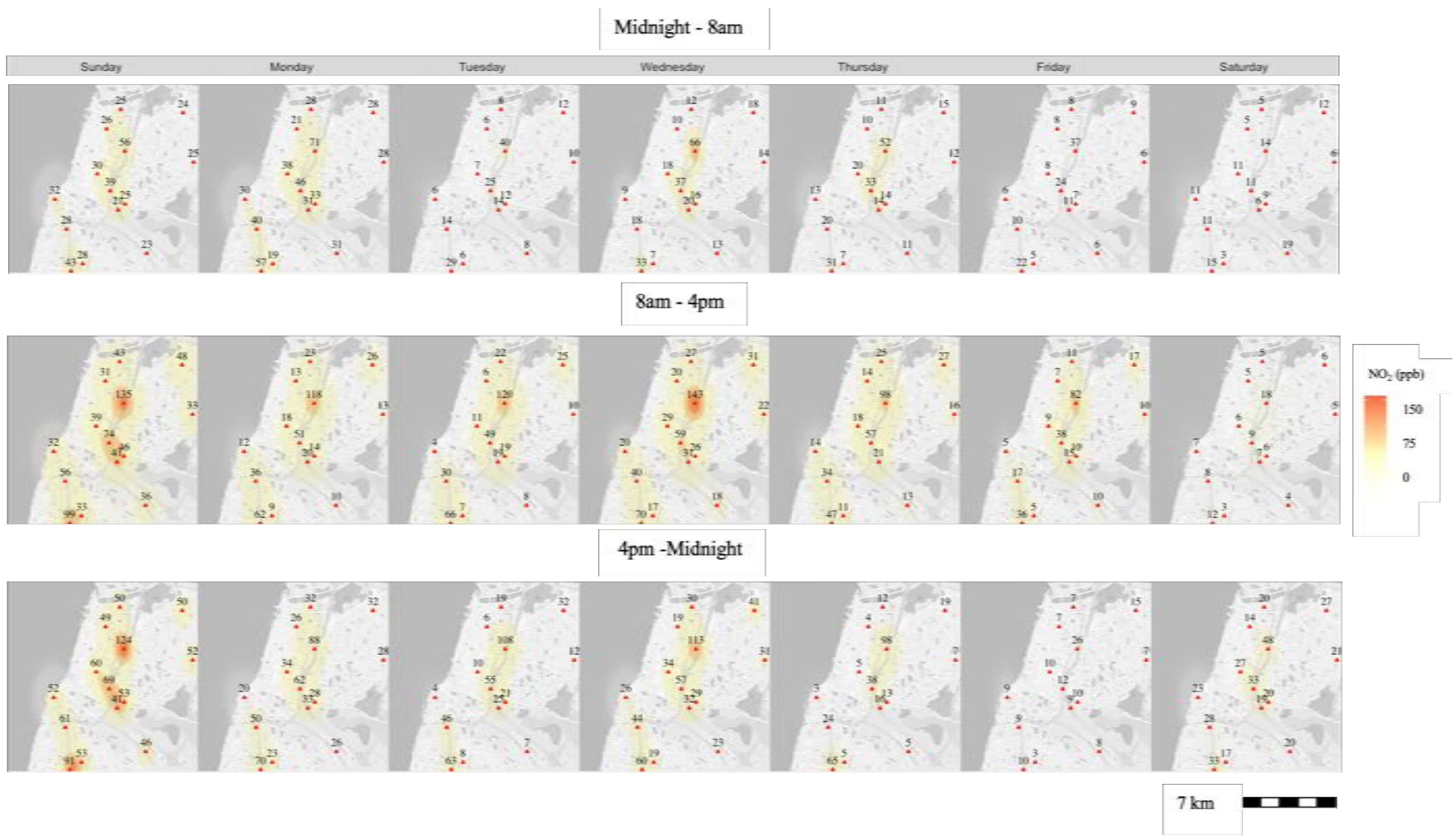


Figure 3: NO_2 Variation Across Time and Space



Notes: Each figure represents the amount of 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 nearby cities.
Map data: Google, Mapa GISrael, 2022.

Table 1: Summary Statistics of Pollution Data

Pollutant	Hour Measured	Units	Monitors	Obs	Average Rate	Standard Error
NO_2	00-08	*ppb*	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	00-08	*Celsius*	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	00-08	m/sec	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
$PM_{2.5}$	00-08	$\mu g/m^3$	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	00-08	*ppb*	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	00-08	*ppb*	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}	00-08	$\mu g/m^3$	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	00-08	*ppm*	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-minute interval measurement.

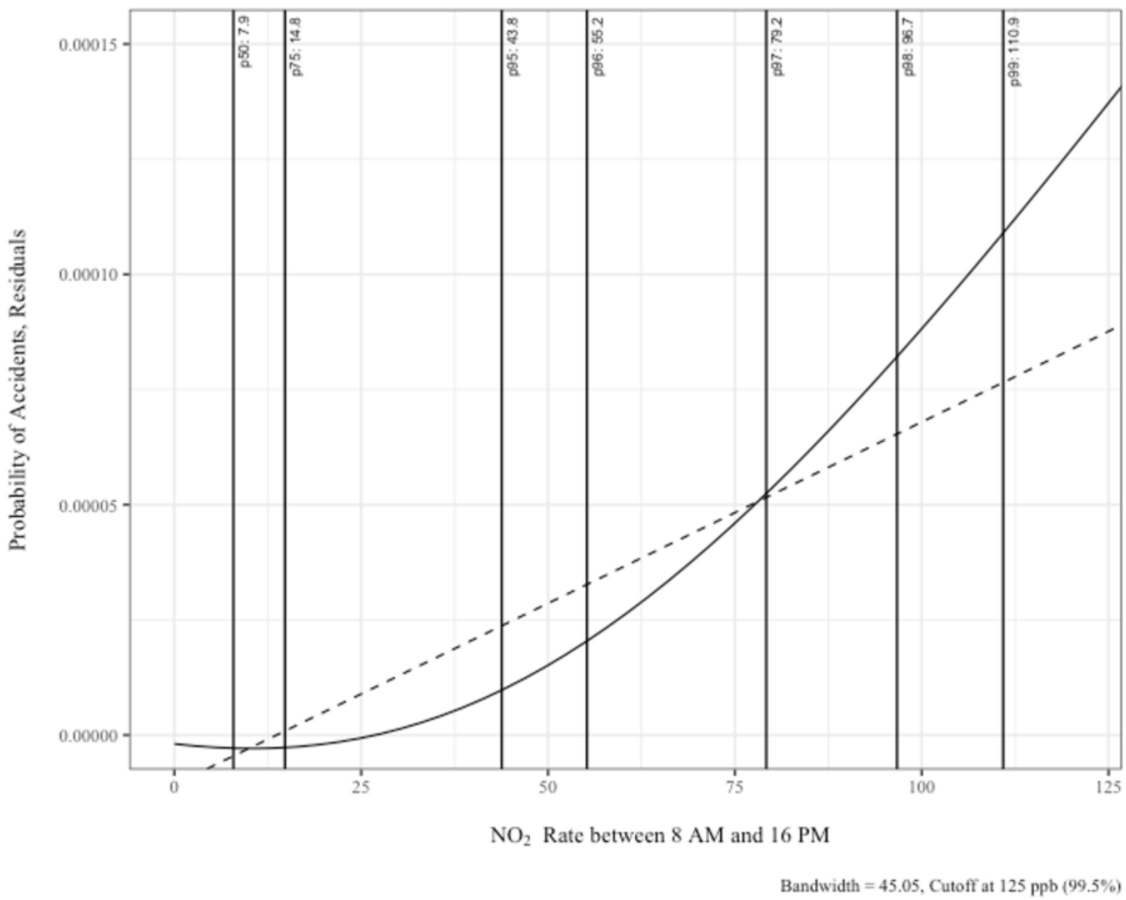
Table 2: Effect of NO_2 on the Probability of a Construction Work Accident

	OLS		Instrument:		Non-linear	
			Average NO_2 Levels in 5-10 km Radius	NO_2 Levels Between Midnight-8 AM		
	(1)	(2)	(3)	(4)		(5)
NO_2	0.0039***	0.0033***	0.0037**	0.0040***	99th Perc.	4.33**
	(0.011)	(0.012)	(0.017)	(0.015)		(1.715)
					95th Perc.	1.586
						(1.076)
Kliebergen-Paap Wald F-statistic			1,435.3	1,855.4		
Reduced Form			0.0026**	0.0031***		
			(0.0012)	(0.0012)		
Weather Controls	Yes	Yes	Yes	Yes		Yes
Time FE	Yes	Yes	Yes	Yes		Yes
Site FE	Yes	Yes	Yes	Yes		Yes
10 *ppb* Increase on Prob. of Accident	30%	25%	28%	31%	99th Perc.	377%
					95th Perc.	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 dummy variables of the year, month, and day of the week. Weather variables include wind, humidity percentage, temperature rate, and equivalent squared variables. For the non-linear 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 a.m. in the closest monitor with a NO_2 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 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



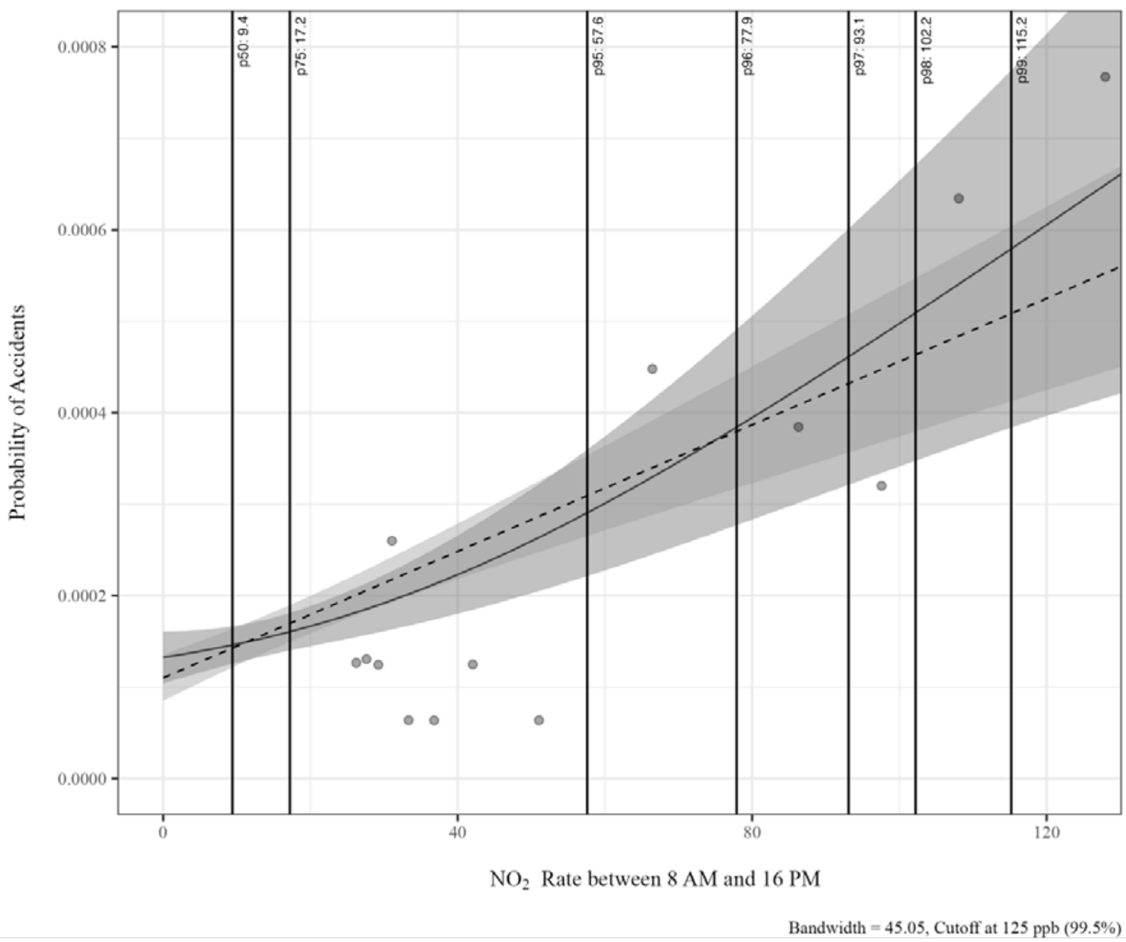
Notes: The continuous line represents the semi-parametric estimation of the connection between NO2 levels at the closest measuring station and the probability of an accident at a construction site. The dashed line represents the liner connection.

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 NO_2 Rate in 5-10 km Radius	Instrument: NO_2 Rate Between Midnight-8 a.m.	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 dummy variables of the year, month, and day of the week. 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 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 NO_2 levels, above the 85^{th} percentile. The dark shaded area represents the 95 percent confidence intervals based on the robust and clustered standard errors that 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 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 × NO_2 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 dummy variables of the year, month, and day of the week. 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 NO_2 levels to the baseline linear model with controls presented in equation 1. The omitted level is the interaction between NO_2 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 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 NO_2. 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 NO_2 level according to our nonparametric estimate; see paper for details. The 95% confidence intervals are calculated using a bootstrap estimation method.

A Online Appendix

Appendix Table A1: Correlations Between Air Pollutants and Weather Variables

Panel A: Linear

	NO_2	$PM_{2.5}$	SO_2	O_3	Temperature	Wind	Humidity
NO_2	1	-	-	-	-	-	-
$PM_{2.5}$	0.21	1	-	-	-	-	-
SO_2	0.55	0.15	1	-	-	-	-
O_3	-0.49	-0.02	-0.17	1	-	-	-
Temperature	-0.12	0.17	-0.1	0.41	1	-	-
Wind	-0.15	-0.04	-0.09	0.2	-0.03	1	-
Humidity	-0.21	-0.16	-0.24	-0.17	-0.41	0.12	1

Panel B: 95^{th} Percentile

	NO_2	$PM_{2.5}$	SO_2	O_3	Temperature	Wind	Humidity
NO_2	1	-	-	-	-	-	-
$PM_{2.5}$	0.03	1	-	-	-	-	-
SO_2	0.19	0.01	1	-	-	-	-
O_3	-0.02	0.04	0	1	-	-	-
Temperature	0.02	0.05	0	0.16	1	-	-
Wind	-0.02	0.13	-0.01	0.01	-0.02	1	-
Humidity	-0.02	0.02	-0.04	-0.03	-0.05	0.08	1

Note: The correlations presented are computed on the sample of all pollution monitors readings for each day between 1 January 2017 and 19 November 2019, where each day corresponds to the measurements between 8 a.m. and 4 p.m. For Panel A, the correlation is between the reading's linear values, and for Panel B, between binary variables that equal 1 if the level exceeds the 95^{th} percentile value for that variable and equals zero otherwise.

Appendix Table A2: 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 (1)	Small Company (2)	Interaction (3)
NO_2	0.190***	0.246***	0.237***
	(0.011)	(0.008)	(0.007)
NO_2 $\times$			-0.016
Big Company			(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 NO_2 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, the average NO_2 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 whose 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 dummy variables of the year, month, and day of the week. 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.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.001$

Appendix Table A3: The Effect of Nitric Oxide (NO) on the Probability of a Construction Accident

	(1)	(2)	(3) Instrument: Average Rate in 5-10 km Radius	(4) Instrument: Rate Between Midnight-8 a.m.		(5) Non-linear
NO	0.0050***	0.0039**	0.0056*	0.0032*	99^{th} Perc.	0.347**
	(0.0002)	(0.0002)	(0.0003)	(0.0002)		(0.143)
					95^{th} Perc.	0.0524
						(0.058)
Reduced Form			0.0045*	0.0049*		
			(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} Perc.	302%
					95^{th} Perc.	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 a.m. and 4 p.m. and multiplied by 1,000 for ease of reading. Time-fixed effects contain the dummy variables of the year, month, and day of the week. Weather variables include the wind, humidity percentage, temperature rate, and the equivalent squared variables. For the non-linear regression, the levels are the NO AQI moderate and unhealthy for sensitive group rates, which correspond roughly to the 99^{th} and 95^{th} 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 a.m. and 4 p.m. The second instrument is the rate between midnight and 8 a.m. 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.

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Appendix Table A4: Regressions Including NO_2, $PM_{2.5}$, O_3, and SO_2 Together

	(1)	(2)
NO_2	0.0043***	0.0046
	(0.00015)	(0.0039)
1 SD increase	66.8%	56.6%
$PM_{2.5}$	-0.0011	-0.0015
	(0.0011)	(0.00025)
1 SD increase	-13.2%	-16.2 %
O_3		0.0043
		(0.0029)
1 SD increase		38.2%
SO_2		0.0008
		(0.0022)
1 SD increase		0.64%
Clusters	3,649	1,409
Observations	1,261,425	426,019

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 dummy variables of the year, month, and day of the week. Weather variables include wind, humidity percentage, temperature rate, and equivalent squared variables. Standard errors are robust and adjusted for clusters by construction sites.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Appendix Table A5: Testing Robustness due to Possible Spatial Auto-Correlation and Correcting for Multiple Hypothesis Testing

	(1)	(2)	(3) Instrument: Average Rate in 5-10 km Radius	(4) Instrument: Rate Between Midnight - 8 a.m.		(5) Non-linear
NO_2	0.0039	0.0033	0.0037	0.0040	99^{th} Perc.	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	{0.0014}***	{0.0017}**	{0.0017}**	{0.0015}***		{0.208}**
					95^{th} Perc.	0.159
						(0.108)
						[0.051]***
						{0.089}*
					99^{th} Perc.	
p-value	0.00	0.00	0.03	0.00	p-value	0.01
q-value	0.00	0.01	0.06	0.01	q-value	0.02
					95^{th} Perc.	
					p-value	0.14
					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 dummy variables of the year, month, and day of the week. Weather variables include wind, humidity percentage, temperature rate, and equivalent squared variables. For the non-linear regression, the levels are the NO_2 AQI moderate and unhealthy for sensitive group rates, which correspond roughly to the thresholds of the 99^{th} and 95^{th} 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 a.m. 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 round parentheses, adjusted for clusters by monitors appear in squared parentheses, and Conley (1999) standard errors which account for spatial correlation appear in curly parentheses, using a 0.69 km radius. The q-value is the sharpened False Discovery Rate (FDR) corrected for multiple hypotheses testing the effect of $PM_{2.5}$.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Appendix Table A6: The Effect of $PM_{2.5}$ and NO_2 on the Probability of a Construction Accident

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A:								
$PM_{2.5}$	0.0039***	0.0039***	0.0034**	0.0030*	0.0030*	0.0030*	0.0036**	0.0009
	(0.0015)	(0.0014)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0011)
Panel B:								
NO_2	0.0040***	0.0041***	0.0036***	0.0034**	0.0032**	0.0034**	0.0043***	0.0037***
	(0.0012)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0014)	(0.0014)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	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	3,649	3,649	3,649	3,649	3,656	3,649	3,649	3,649
Observations	1,261,425	1,261,425	1,261,425	1,261,425	1,261,425	1,261,425	1,261,425	1,261,425

Notes: The dependent variable is the probability of an accident occurring at the construction site. The coefficient stated belongs to the independent variable, which in Panel A is $PM_{2.5}$ in $\mu g/m^3$ units between 8 a.m. and 4 p.m., and in Panel B is the rate of NO_2 between the same hours in ppb units, both in a monitor closer than 1 km distance. 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.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.001$

Appendix Table A7: 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.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.001$

Appendix Table A8: Variation Under Various Sets of Fixed Effects

	NO_2			$PM_{2.5}$			Temperature		
		(1)			(2)			(3)	
Control variable added:	R^2	σ_e	$\lvert e\rvert > 1/7$ SD	R^2	σ_e	$\lvert e\rvert > 1/7$ SD	R^2	σ_e	$\lvert e\rvert > 1/7$ SD
No FE	-	36.466	0.865	-	17.978	0.998	-	6.105	0.999
Wind	0.021	36.088	0.840	0.001	17.965	0.852	0.059	5.923	0.924
Temperature	0.031	35.889	0.830	0.021	17.792	0.850	-	-	-
Humidity	0.032	35.871	0.830	0.033	17.678	0.854	0.203	5.450	0.907
Year	0.033	35.863	0.830	0.034	17.672	0.853	0.207	5.435	0.907
Month	0.070	35.159	0.808	0.106	17.002	0.826	0.818	2.604	0.688
Day of the Week	0.106	34.483	0.775	0.116	16.906	0.827	0.819	2.595	0.688
Region	0.187	32.877	0.741	0.156	16.518	0.813	0.860	2.285	0.647
City	0.300	30.509	0.687	0.246	15.610	0.789	0.877	2.138	0.623
Site	0.759	17.893	0.575	0.56	11.925	0.740	0.885	2.071	0.609
Observations		2,189,124			1,261,425			1,684,471	

Notes: This table summarizes regressions of nitrogen dioxide, particulate matter, and temperature on various fixed effects to show how much variation each one absorbs. Each row adds the fixed effect written in the specific row on top of those that came before. Each group of three columns shows (a) measures of R^2 for the regression, (b) the standard deviation of the residuals (remaining pollution residuals), and (c) the fraction of observations with a residual larger than one-seventh of the standard deviation for each dependent variable. Each dependent variable's analysis is conditioned on the measurement being at most 1 km away from the construction site. All pollutants units are in $\mu g/m^3$, where NO_2 units were converted at 25 degrees Celsius and one standard atmospheric pressure. Temperature is given in Celsius.

Appendix Table A9: Effect of NO_2, $PM_{2.5}$, and Temperature as the Unit of Observation Changes

Independent Variable:	NO_2 (1)	$PM_{2.5}$ (2)	Temperature (3)
Panel A: Construction Site			
	0.00327***	0.000858	0.000822
	(0.00125)	(0.00112)	(0.00409)
1 SD increase	49.20%	9.40%	-3.90%
Clusters (by sites)	5,583	3,649	4,752
Observations	2,189,124	1,261,425	1,684,471
Panel B: City			
	0.0423	0.00471	0.0345
	(0.511)	(0.00877)	(0.059)
1 SD increase	26.80%	-3.50%	10.80%
Clusters (by city)	290	290	290
Observations	146,178	146,178	146,178
Panel C: Country			
	3.604	-1.998	-5.618
	(3.467)	(1.594)	(7.766)
1 SD increase	8.50%	-6.60%	-12.10%
Observations	1,053	1,053	1,053
Mean Dependent by Unit			
Construction Site	0.000129	0.000154	0.000129
City	0.001936	0.001936	0.001936
Country	0.268756	0.268756	0.268756

Notes: This table summarizes regressions of NO_2, $PM_{2.5}$, and temperature in different sizes of unit observation. The coefficients stated belong to the independent variables, which are the pollutants or temperature measurements in the relevant between 8 a.m. and 4 p.m. in ppb, $\mu g/m^3$, and Celsius for NO_2, $PM_{2.5}$, and temperature, respectively, and are multiplied by 1,000 for ease of reading. For Panel A, the dependent variable is whether a construction accident occurred on a given day at the construction site, in Panel B it is the number of accidents that occurred on a given day in the city, and in Panel C it is the number of accidents that occurred in the whole country in the given day. Panel A uses the most granular level of observation, which is a day in a construction site, Panel B aggregates the accidents and takes the mean level of the independent variable in each city per day, Panel C aggregates all of the construction sites in the country per day. In Panel A, all the dependent variable's analysis is conditioned on the measurement being at most 1 km away from the construction site. For the non-linear regressions we consider two cutoff levels for each dependent variable. For the NO_2 and $PM_{2.5}$ in Panels A and B, the levels are the AQI moderate and unhealthy for sensitive group rates, which correspond to 53 and 100 ppb, and 12 and 35 $\mu g/m^3$, respectively. For temperature and Panel C, it is the 95^{th} and 99^{th} percentiles, where the coefficients presented correspond to the more critical of the two.