Journal of Public Economics 251 (2025) 105472

Contents lists available at ScienceDirect

Journal of Public Economics

journal homepage: www.elsevier.com/locate/pubec

Heads up: Does air pollution cause workplace accidents?☆

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HIGHLIGHTS

- We study the causal effect of air pollution on construction-site accidents using daily data from all construction sites and pollution-monitoring stations in Israel.
- We identify nitrogen dioxide (NO_2) as the primary pollutant driving accident risk.
- Effects are significant and highly nonlinear, with moderate NO_2 levels more than doubling accident probability, and levels above 100 ppb nearly quadrupling it, compared to clean-air days.
- Three IV strategies—including lagged pollution, spatial variation, and wind-driven pollution shocks—confirm the causal effect of NO_2 on accidents.
- Effects are exacerbated under conditions of high cognitive strain or reduced awareness.
- A cost-benefit analysis demonstrates potential welfare improvements from subsidizing closures of construction sites on highly polluted days.

ARTICLE INFO

Keywords:
Workplace accidents
Labor productivity
Air pollution
Government policy

ABSTRACT

Literature has shown that air pollution can have short- and long-term adverse effects on physiological and cognitive performance. In this study, we estimate the effect of increased pollution levels on the likelihood of accidents at 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 causal effect of nitrogen dioxide (NO_2), one of the primary air pollutants, on 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 %. Importantly, our findings suggest that these effects are non-linear. While moderate pollution levels, according to EPA standards, compared to clean air levels, increase the likelihood of accidents by 138 %, unhealthy levels increase it by 377 %. We present a mechanism where the effect of pollution is exacerbated under conditions of high cognitive strain or reduced awareness. Finally, we perform a cost-benefit analysis, supported by a nonparametric estimation calculating the implied number of accidents due to NO_2 exposure, and examine a potential welfare-improving policy to subsidize the closure of construction sites on highly polluted days.

1. Introduction

With 9 out of 10 people worldwide breathing polluted air and an estimated 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 (World Health Organization, 2018). Given this, the effects of air pollution on society are a focus of a growing literature in many disciplines,

☆ We thank the Ministry of the Environment and the Ministry of the Economy for providing the data for this study and for their guidance in interpreting the pollution measures. We also thank the geography lab at the Social Science Faculty at the Hebrew University for their assistance with data geo-coding and Ludovica Gazze, Walker Hanlon, Jonathan Guryan, Ro'ee Levy, Steve Pischke, Sefi Roth, and participants at various seminars for comments and useful suggestions. Genia Rachkovski acknowledges support from the Pinhas Sapir Center for Development. Finally, we thank the editor, Joseph Shapiro, and three anonymous referees for their valuable comments, which greatly improved the paper.

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https://doi.org/10.1016/j.jpubeco.2025.105472
Received 10 December 2024; Received in revised form 14 August 2025; Accepted 17 August 2025
Available online 7 October 2025

including economics, which 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 and understudied factors affecting labor-market productivity. 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, in 2017, the costs of work-related accidents and illnesses accounted for around 3.3 % 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. Using regularization methods and multiple regression analysis, out of several major pollutants measured, including NO_2, $PM_{2.5}$, O_3, and SO_2, we identify that the most significant effect on construction-related injuries and fatalities originates from nitrogen dioxide (NO_2), a primary, although less studied, air pollutant.[2]

We find that a 10-ppb increase in NO_2 levels increases the likelihood of an accident by 25 %, where the mean NO_2 level in our sample is 13.7 ppb during working hours and the baseline accident rate is 1.29 per 10,000 site-working days.[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 bounds of which correspond roughly to the 95th and 99th percentiles in our sample. At these levels, the likelihood of an accident is increased by 138 % and 377 %, 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 flexibly 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 co-generation 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 at 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 reach 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 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, as an instrument for pollution. 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 and workers are not on site. Further, these pollution levels, measured the night before, should only affect the probability of a construction accident occurring at 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 % and 31 % 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 all four major pollutants measured (NO_2, $PM_{2.5}$, SO_2, and O_3), instead of NO_2 as the instrumented variable. This analysis alleviates concerns regarding the possibility of under-identification due to the diversity of pollutants that might be highly correlated with the instrumented pollutant and potentially directly affect the outcome variable.

An additional concern to the causal interpretation of our findings is the potential existence of shocks that simultaneously raise pollution and accident risk over a broader area—say, an uptick in regional economic activity or traffic surges that both elevate pollution levels and make workers more accident-prone. To tackle this, we collect data on Israel's 50 most polluting plants in our time frame and their geographical location, and exploit day-to-day wind direction.[5] Whenever the prevailing wind blows from a given plant toward a construction site, it exogenously elevates that site's pollution relative to days when the wind blows elsewhere, allowing us to instrument for NO_2 levels. Additionally, the variation in the type of emissions of the different plants also allows us to simultaneously instrument for both NO_2 and $PM_{2.5}$ using the same "wind-from-plant" IV strategy. Reassuringly, our third IV approach yields the same pattern we see throughout the paper: a clear, statistically significant effect of NO_2 on accident likelihood under various specifications of angle bins and distance cutoffs between plants and construction sites, while $PM_{2.5}$ shows no independent impact.

As a next step, we focus on the potential mechanisms of the effect. The physiological properties of NO_2 make it particularly relevant for workplace safety. As a respiratory irritant, it causes immediate effects, including impaired oxygen exchange and reduced alertness that can manifest within hours of exposure. By examining the interaction 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 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.

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

[5] Based on air pollution levels reported in Israel's Environmental Impact Index, the top 50 industrial facilities account for approximately 71 % of measured pollution from the largest industrial facilities monitored by Israel's Environmental Protection Agency, while the remaining facilities contribute increasingly smaller amounts. Since the manufacturing and construction sector represents approximately 12 % of total NO_x emissions nationally (Ministry of Environmental Protection, 2023), we estimate these facilities represent roughly 8 % of Israel's total NO_x emissions.

NO_2 levels with worker alertness (proxied by day of the week), we provide suggestive evidence that the detrimental effect of NO_2 on accidents is exacerbated under conditions of strenuous physiological states of the workers. Our setting and the findings 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 in our setting when controlling for construction site fixed effects. In contrast, the effect of NO_2 remains robust.[6] This distinction may stem from NO_2's potential to cause acute respiratory irritation and modest cognitive impairment within hours, whereas $PM_{2.5}$'s impacts tend to accumulate more slowly; we explore these physiological pathways in more detail in the paper.

We further 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, and 5 km, 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 each contractor to shut down their daily operations. Our estimations show 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 workers' insurance payouts are large enough to offset losses from construction site shutdown costs for the day.

Finally, using a back-of-the-envelope calculation based on our nonparametric estimates of accident probabilities at different levels of NO_2, we impute the number of additional accidents attributable to NO_2 exposure relative to clean-air conditions. We estimate that high-pollution days account for approximately 14 % of all reported construction-site accidents, translating into a substantial increase in annual insurance costs.

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 Israeli context 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 presents 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).[7] 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 study contributes to the existing literature by examining the relationship between air pollution and workplace accidents. This area has received relatively less attention but holds significant relevance for labor outcomes and highlights the pervasive effects of pollution, including in decisions with high-stakes, life-changing outcomes such as severe workplace injuries. Specifically, we identify nitrogen dioxide (NO_2) as the most influential, though previously less emphasized, pollutant and explore potential mechanisms of its effect. The papers most closely related to ours are the concurrent paper by Cabral and Dillender (2024) and the paper by Chambers (2021), which find a connection between increased particulate matter and workplace accidents. The design of our study allows us to identify the plausibly causal effects of several primary pollutants, including NO_2, $PM_{2.5}$, SO_2, and O_3, and as a result to identify the importance of NO_2 and its detrimental effects.

Another notable advantage of the study is the detailed and spatially distributed granular data on pollution levels, which is enabled by an extensive network of monitoring stations near the construction sites in our sample. These detailed data reduce the risk of measurement error bias, enhancing the robustness of our findings. As a result, we observe stronger effects of pollution on workplace accidents compared to prior studies, underscoring the importance of developing effective mitigation policies.

Importantly, as research has primarily focused on the health effects of air pollution among young children and the elderly, our focus on construction workers highlights an identified adverse effect of air pollution on the working-age population. Therefore, we provide evidence that the costs of pollution extend beyond vulnerable populations to include productivity losses from workplace accidents. Lastly, we include a cost-benefit analysis to provide practical insights into the implementation of such interventions.

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, along with the top pollution sources in Israel; 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.[8] 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

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

[7] Deschenes et al. (2017) also find significant effects of reductions in nitrogen oxides (NO_x) pollution on respiratory medication usage and mortality.

[8] 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.

Fig. 1. Spatial distribution of air quality monitors and active construction sites in Israel. *Notes*: This figure plots the geographical distribution of active construction sites (circles) and pollution monitoring stations (triangles) across Israel. Data source: Israel's Environmental Protection Ministry, the Israeli Ministry of Economy and Industry, and the authors' geolocation data.

site, which resulted in our final sample of 24,614 sites and 10,016,000 observations.[9]

The accident sample that the Ministry of Economy and Industry provided included 1316 accidents during the sample period. The accidents provided by Kav LaOved, a workers' rights organization that receives reports of accidents not properly filed with authorities, did not include site IDs matching the ministry's data.[10] We matched the accidents to the sites by their addresses instead, which resulted in an additional 31 accidents.[11] Merging the dataset of the site's active days sample and the accidents sample, we were left with 1164 accidents per 10,016,000 working days in construction sites.[12]

Fig. 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 Fig. 2, we can see that construction accidents occur across all days of the week, with a substantial drop on Fridays and Saturdays.[13] 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.[14]

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, with the same reporting schedule. The monitoring station locations are spread out across the country, as seen in Fig. 1. Monitoring stations in urban areas account for 37 % of all monitoring stations, rural for 30 %, and suburban for 11 %. Monitoring stations near trains/roads account for 18 %, and industrial areas for 4 %.

Each active day in a construction site is assigned the nearest reading for each variable, where 21,861, 15,440, 12,677, and 7199 construction sites have at least one monitoring station at a 5, 2, 1.5, and 1 km distance, respectively. At our primary 1 km threshold specification, we retain 5583 construction sites, which are at a 1 km range of an NO_2 monitor, and 283 accidents. This proportional reduction in accidents suggests no systematic relationship between accident rates and proximity to monitoring stations.

The primary source of NO_2 pollution is fuel combustion from transportation and industrial work, with transportation alone accounting for nearly 90 % of NO_2 emissions in population centers in Israel, according to the Israeli Ministry of Health (Ministry of Environmental Protection, 2023). 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. Fig. 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.

Lastly, for our analysis of major polluting sources in Israel, we also use data from the Environmental Impact Index, Annual Reports for the year 2018. The Israeli Ministry of Environmental Protection publishes this report annually, which quantifies and ranks industrial facilities based on their environmental footprint and potential risk to the surrounding area. Appendix Fig. A1 shows the locations of those major pollution sources in Israel with respect to the air quality monitors.

Table 1 shows summary statistics for pollution and weather variables in our dataset, while Appendix Table A1 presents the correlation matrix related to those variables. In 2017, the European

[9] 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 a lack of exact matching of 957 sites' addresses in the geo-coding process.

[10] From our institutional understanding, it is a manager's responsibility to report an accident; thus, the Kav LaOved also includes accidents that were misreported, complementing the reported accidents.

[11] Our main estimates remain robust to the exclusion of Kav LaOved's accidents.

[12] 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.

[13] The workweek in Israel starts on Sunday, while Friday and Saturday are weekend days, equivalent to Saturday and Sunday in most of the Western world.

[14] 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 1103 and 3270 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.

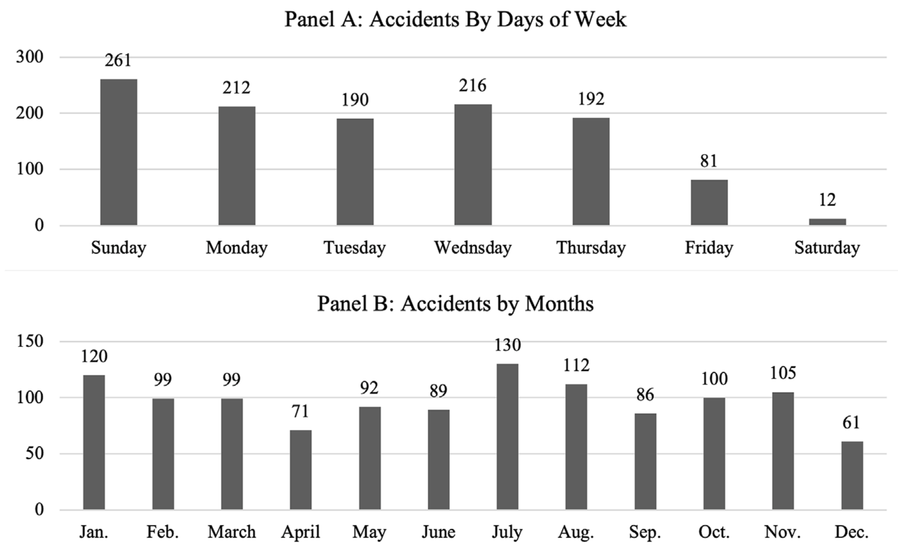

Fig. 2. Distribution of construction accidents.

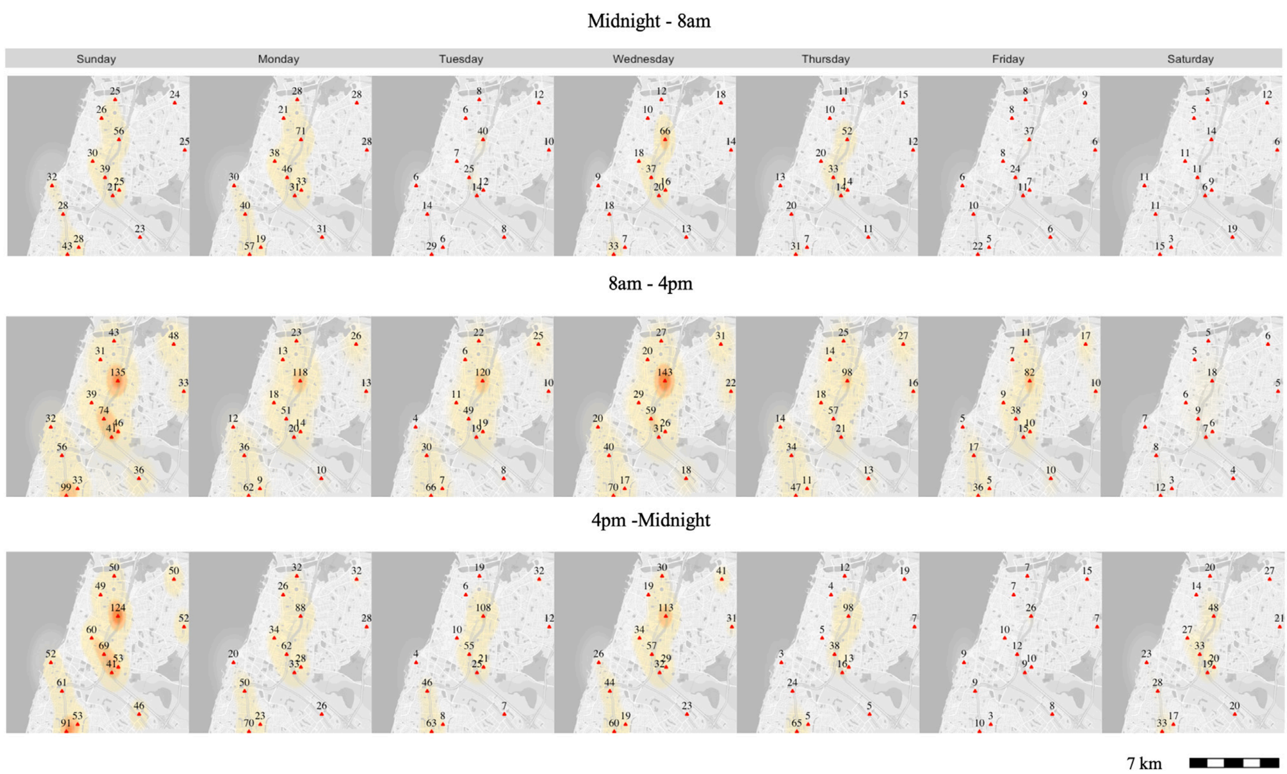

Fig. 3. NO_2 variation across time and space. *Notes*: Each figure represents the amount of NO_2 measured at each of the monitoring stations (shown as triangles) in 8-hour intervals for each day of the week from January 21st to January 28th, 2018. The color shown next to each monitor is determined by 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. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Environmental Agency reported an annual mean average of 22.0 $\mu g/m^3$ for NO_2 across the European Union states,[15] 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 time span. 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

[15] Data is from a 2019 report by the European Environmental Agency (accessed July 17, 2022).

Table 1
Summary statistics of environmental data.

Variable	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
$PM_{2.5}$	00–08	μg/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
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

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 measurements.

and very similar to levels in the US and those recommended by the WHO.[16]

4. Econometric strategy – identification

4.1. Baseline linear probability model

In our primary specification, we examine the partial correlation between pollution levels and construction accidents using a linear probability fixed effects model[17]:

$$Y_{st} = \beta Pol_{st} + f(Temp_{st}, Wind_{st}, Hum_{st}) + S_s + DMY_t + \varepsilon_{st}, \quad (1)$$

where s indexes the construction site and t the day. Y_{st} denotes the probability of an accident, Pol_{st} is the level of pollution at the monitoring station closest to the construction site (up to 1 km) in a given time interval. 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 is measured at the closest monitoring station. ε_{st} is the idiosyncratic error term. Standard errors are clustered at the pollution monitor level.[18]

There are several potential threats to inferring a causal relationship between pollution and construction accidents estimated by Eq. (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.[19]

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. This allows us to focus on variation within the construction site regarding 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).[20]

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

[16] 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/m^3 averages (Negev, 2020).

[17] We preferred to use the linear probability model over maximum likelihood estimators (MLE) as our main specification, as the MLE estimation creates endogeneity by omitting construction sites where no accidents occurred during our sample period (for an in-depth discussion on this issue, refer to Autor et al. (2014)). Nevertheless, the effects of pollution remain highly significant when using Probit, Logit, and Poisson estimation for the same sample.

[18] As construction sites are assigned to their closest monitor's reading within 1 km, in some cases, multiple construction sites use the same pollution monitoring data, which might generate spatial and temporal autocorrelation. Clustering at the monitor station level allows us to address this issue and take into account the actual location where the pollution was measured.

[19] Our results are robust to the inclusion of weather controls and to specifications using different functional forms of the weather variables—such as linear, quadratic, higher-order polynomials, decile dummies, or lagged—suggesting that weather controls do not play a significant role in the estimation of the effects of pollution in this context (see Appendix Table A2).

[20] 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.

Table 2
All pollutants and penalized linear regression.

	All pollutants (1)	NO_2 and $PM_{2.5}$ (2)	Lasso λ - min (3)
NO_2	0.0077***	0.0042***	0.0047
	(0.00026)	(0.0014)	
1 SD increase	141.3 %	63.2 %	
$PM_{2.5}$	−0.0022	−0.0013	0
	(0.0016)	(0.0009)	
1 SD increase	−30.8 %	−19.6 %	
O_3	0.0034		0
	(0.0025)		
1 SD increase	26.4 %		
SO_2	0.0175		0
	(0.0230)		
1 SD increase	12.4 %		
Weather Controls	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Site FE	Yes	Yes	Yes
Construction Sites	1858	3838	
Observations	630,523	1,387,628	630,523

Notes: In columns 1 and 2 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 1000 for ease of reading. Time-fixed effects contain the dummy variables for the year, month, and day of the week. Weather variables include wind, humidity percentage, temperature rate, and equivalent squared variables. The sample includes readings that were measured from a closer distance than the 25th percentile, for each pollutant separately, from the construction site (1, 1.4, 1.5, and 1.4 for NO_2, $PM_{2.5}$, O_3, and SO_2 respectively. Standard errors are robust and adjusted for clusters by construction sites. In column 3, the LASSO is estimated on the residualized pollutants. The package used is glmnet in the statistical software R. Zeros indicate the shrunk variables. The penalty parameter λ is optimally chosen to minimize the mean squared errors. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

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. While our data show no change in the number of monthly workers with mean NO_2 levels (corr = –0.055), this test may be too coarse to capture day-to-day "sick-day" absenteeism, allowing for the possibility that such short term absenteeism might be part of the effect and amplify our estimated pollution-accident link accordingly. However, our institutional discussions suggest that workers and contractors are not likely to track air pollution or be aware of its specific impacts on accidents or act upon them, making large systematic absentee responses less likely.[21]

In the paper, we focus mainly on the effects of NO_2. This choice is driven by our findings presented in Table 2. In columns (1) and (2) we show that when considering a single "horse-race" regression, NO_2 is the sole significant pollutant which also has by far the largest effect on the probability of an accident when compared to other major pollutants measured.[22] While column (1) combines all pollutants in our dataset, column (2) includes only NO_2 and $PM_{2.5}$, which are the both the most studied and monitored. Both analyses point to our aforementioned conclusion remaining unchanged.[23] In column (3), we further show that a LASSO sample selection procedure, with a penalized parameter optimally chosen to minimize the mean squared errors, only selects NO_2 as a relevant pollutant while omitting all other pollutants measured.[24]

The difference in the observed effect of NO_2 compared to other pollutants might be due to several reasons. First, the physiological effects of exposure to NO_2 might have a greater effect in this setting. We discuss this possibility in detail in a later section. Second, 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 higher number of monitors is possibly due to the denser regulatory siting requirements for NO_2 monitors, driven by their spatial variability properties, and their cost-effective nature. This allows us to estimate our results more accurately at a larger number of locations across Israel.[25] Furthermore, compared to other pollutants, NO_2 introduces significant spatial variability, allowing us to capture the effect more precisely (Hewitt, 1991).[26]

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 occurring on busy or specific days when the likelihood of an accident increases, might also drive our results. Another concern is that other time varying local factors, such as economic activity can affect both pollution levels and the probability of accidents. We implement an instrumental variable approach to deal with these potential concerns 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 company's

[21] Avoidance behavior is also less likely to occur in any asymmetric way related to the proneness to accidents. See also Salehi Sichani et al. (2011), who find no correlation between tenure at work and absenteeism in the industrial construction workforce.

[22] The sample considered restricts NO_2 and $PM_{2.5}$ readings to at most 1 and 1.4 km respectively, from the corresponding construction site (corresponding to the 25th percentile of each pollutant's measurement distance). The analysis is robust to considering different distance cutoffs.

[23] As NO_2 and the other pollutants might be endogenous in this regression, we explore the robustness of the effects of NO_2 to the multiplicity of pollutants and the use of a general measure of pollution such as AQI in later sections of this paper.

[24] We find a similar pattern of results in which the effect of NO_2 is significantly stronger in a multi-pollutant regression and is solely chosen in the LASSO regressions for various nonlinear specifications, such as in the case where we define the pollutants as dummy variables equal to 1 when pollution levels exceed a range of percentiles in our sample.

[25] The relatively larger number of NO_2 monitoring stations is unlikely to drive the observed difference in effects. As shown in column (8) of Appendix Table A3, when we restrict the sample of our analysis only to monitoring stations which have both NO_2 and $PM_{2.5}$ monitors, the estimated NO_2 effect remains virtually unchanged. By contrast, $PM_{2.5}$ shows no significant effect.

[26] In this paper, our aim is not to rule out the possibility of an effect of other pollutants in various contexts, but rather to highlight the importance of monitoring exposure to NO_2, its detrimental effects, the mechanisms of the effects and potential solutions. In Section 7 we go further in the attempt to differentiate the effects of various determinants implicated for their potential effects in similar contexts.

limited liability status, a proxy for construction site size, and find no evidence that large-sized construction sites affect pollution in this range.[27] 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, the analysis of these instrumental variables is represented by
First stage:

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

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

Second stage:

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

where we instrument pollution levels at the monitoring station closest to the construction site s first in Eq. (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 Eq. (3) with the NO_2 levels measured by the average of stations in a 5–10 km radius of the construction site ($NO_{2,g(5-10\ km)st}$). $Pred(NO_{2,st})$ are the values of NO_2 predicted in the first-stage Eqs. (2) and (3).

Despite the advantages of our distance- and lag-based instruments, they may still be vulnerable to omitted-variable bias if broader-scale shocks or unobserved factors shift both pollution and accident risk over larger areas or multiple days. For example, increased economic activity could simultaneously increase air pollution and affect workplace accidents through changes in driving patterns, worker absenteeism, or accident reporting behavior (Boone et al., 2011). If such shocks correlate with our instruments, the exclusion restriction would be violated.

To address this concern, we propose a third instrument that exploits exogenous variation in NO_2 by combining pollution from major stationary emitters with random fluctuations in wind direction that carry pollution to construction sites. Our procedure consists of four steps. (1) We identify the fifty most airborne-emission-polluting plants during our sample period, according to the Israeli Environmental Protection Agency.[28] (2) For each construction site, we identify the closest plant and calculate the distance and angle between them.[29] (3) We determine the prevailing wind direction near each plant and classify whether, on a given day, the wind was blowing in the direction corresponding to the angle between the plant and construction site. (4) We create an indicator variable for this wind-alignment condition and use it to instrument for NO_2, testing various specifications of angle ranges and distance cutoffs between plants and construction sites.[30]

Formally, let $\text{PlantWind}_{st}^{deg}$ be an indicator equal to one if on day t the prevailing wind at construction site s blows from the direction of the closest polluting industrial plant in Israel to the closest pollution monitor (i.e., within a degree of $\pm$ 45/60/90° sector from plant to site) and zero otherwise. Under the assumption that wind direction affects accidents only through its impact on local NO_2, we estimate:

First stage:

$$\text{NO}_{2,st} = \sum_{p\in P} \pi_p \, 1_{[P_s=p]}\text{PlantWind}_{st}^{deg} + f(\text{Temp}_{st}, \text{Wind}_{st}, \text{Hum}_{st}) + S_s + \text{DMY}_t + \upsilon_{st} \quad (5)$$

Second stage:

$$Y_{st} = \beta \, Pred(\text{NO}_{2,st}) + f(\text{Temp}_{st}, \text{Wind}_{st}, \text{Hum}_{st}) + S_s + \text{DMY}_t + \varepsilon_{st}, \quad (6)$$

where $1_{[P_s=p]}\text{PlantWind}_{st}^{deg}$ is the exogenous variable, with $1_{[P_s=p]}$ being a dummy that equals one only when plant p is the closest to site s. This form follows Deryugina et al. (2019), and allows us to have plant-specific effects on NO_2 levels when the wind blows from each plant toward the construction sites. $Pred(NO_{2,st})$ is the predicted NO_2 from Eq. (5), $f(\cdot)$ denotes the same flexible weather controls as before, S_s are construction-site fixed effects, and DMY_t are day-of-week, month, and year fixed effects.

This "wind-from-plant" instrument draws on plausibly exogenous wind-direction variation and the geographic location of high-emitting plants, thereby strengthening identification by isolating pollution shocks that are unlikely to be driven by concurrent omitted factors affecting accidents. This instrument is well-powered, and the associated F-statistic stands at 340. Fig. 4 shows that as the wind direction approaches the bearing of the monitor-to-pollution, the effect on the pollution strengthens substantially.

We can also use the "wind-from-plant" instrument to address the issue of multiple pollutants and attempt to differentiate the effect of NO_2. Using pollution monitors in proximity to the emitting plants, we observe that some of the plants are predominantly emitting NO_2, while others are predominantly emitting $PM_{2.5}$. In Appendix Figure A3 we present the added pollution of NO_2 and $PM_{2.5}$, for each of the plants in our list, to demonstrate this variation. We can exploit this variation to extend our "wind-from-plant" instrument to instrument separately for each pollutant.[31] The first-stage of both pollutants is strong and stands at approximately 200.

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

[27] In Appendix Table A4, 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 larger construction sites. We find that these estimates are not statistically significantly different from each other.

[28] This top 50 cutoff represents a natural threshold around the median pollution level of the listed plants. Our results are robust to alternative specifications.

[29] Appendix Figure A1 shows the distribution of these plants and the air quality monitors.

[30] We also attempted the classic sector-based downwind IV approach following Deryugina et al. (2019), using broad wind-direction bins alone (see Appendix Figure A2). However, NO_2 concentrations diminish relatively quickly with distance, leading to high spatial variation. Combined with Israel's smaller geography, these properties make this approach less effective, as large-scale wind sectors induced almost no first-stage variation. Appendix Figure A2 illustrates this weak relationship by plotting the daily downwind indicator against measured NO_2.

[31] Using this approach we can differentiate the effect of NO_2, the main focus of this study, and the effect of $PM_{2.5}$, which is consistently highlighted in this literature. We are unable to extend this analysis to include other pollutants due to the lack of sufficient variation in this approach to separately identify their potential effects.

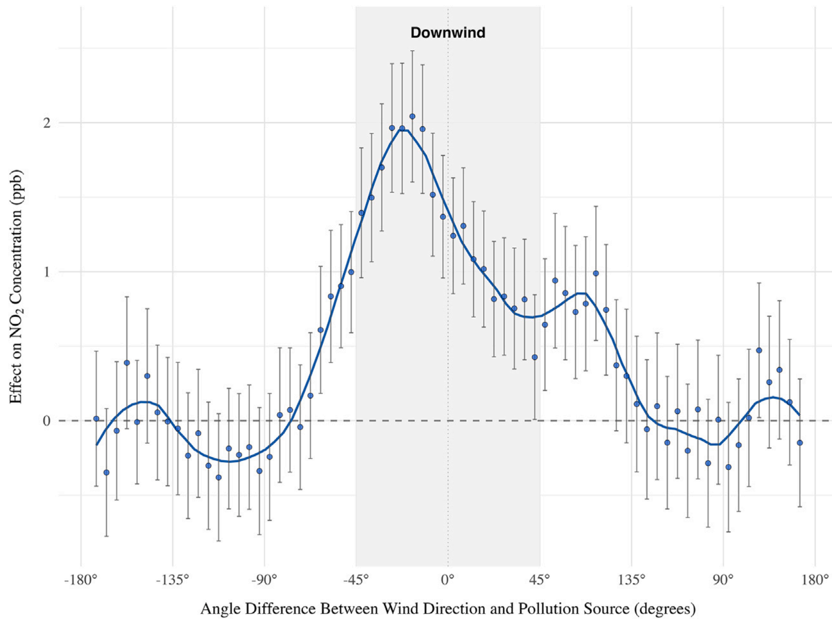

Fig. 4. Wind blowing from pollution source to monitor. *Notes*: This figure plots the coefficient of 5-degree bins of the daily difference between the wind and monitor to pollution source angle on the level of NO_2. All regressions include weather and time fixed effects, which contain year, month, and day-of-the-week dummies, as well as monitor and pollution source fixed effects, along with weather controls (wind, humidity percentage, temperature rate, and equivalent squared variables). The sample is restricted to the closest pollution source for each monitor, which is at most a 25 km distance. Each coefficient is accompanied by its corresponding 95 % confidence intervals, which are heteroskedastic robust.

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.[32] 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 Eq. (5), we substitute the continuous measure of air pollution in Eq. (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 days as days when NO_2 levels are higher than 100-ppb by EPA standards, corresponding roughly to the 99th percentile in our sample.[33] Formally,

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

where $Moderate NO_{2,st}$ is a dummy variable equal to 1 when NO_2 levels are between 53 and 100-ppb, and $High NO_{2,st}$ 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 adopt 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 across 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 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 Eq. (1). In Table 3, columns (1) and (2), we report the correlation between a continuous measure of NO_2 using OLS without controls and with controls for weather, 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 % and 30 % 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 % 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.

5.1. Instrumental variable results

In columns (3) and (4) of Table 3, we present the results of our distance- and lag-based instrumental variable estimation as outlined in

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

[33] 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 + .

Table 3
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 a.m.		
	(1)	(2)	(3)	(4)		(5)
NO_2	0.0039***	0.0033***	0.0037**	0.0040***	99th Perc.	0.4330***
	(0.0004)	(0.0010)	(0.0016)	(0.0013)		(0.0446)
					95th Perc.	0.1586***
						(0.0508)
Wald F-statistic			21.8	13.0		
Reduced Form			0.0026*	0.0031**		
			(0.0015)	(0.0012)		
Weather Controls	No	Yes	Yes	Yes		Yes
Time FE	No	Yes	Yes	Yes		Yes
Site FE	No	Yes	Yes	Yes		Yes
10 ppb Increase on Prob. of Accident	30 %	25 %	29 %	31 %	99th Perc.	335 %
					95th Perc.	123 %
Construction Sites	5583	5583	5274	5583		5583
Observations	2,189,124	2,189,124	2,075,280	2,169,852		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 1000 for ease of reading. Time-fixed effects contain the dummy variables for 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 95th and 99th percentiles (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 NO_2 pollution monitor, and appear in parentheses. The effect of 10-ppb is compared to the average accident rate in each regression. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

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 % (SE = 13 %) and 31 % (SE = 12 %) when instrumenting for NO_2 pollution levels at the closest monitoring station with pollution levels derived from the average of the pollution levels measured at stations within 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 % level, while the estimate when using the IV of the pollution levels measured at stations within a radius of 5–10 km is significant at the 5 % level.[34] The first stage for both instruments is strong, with an F-statistic of 21.8 and 13, respectively.[35]

We further acknowledge that there is a threat that pollution may not entirely dissipate overnight. That is, if there are days of intense activity at the construction site and pollution is high, it might result in higher pollution levels the morning after as well. To rule out the possibility of this scenario, we have also restricted our lagged instrumental specification to the first day of the working week (Sunday). Our results remain robust under this specification.

Columns (1)–(4) of Table 4 report our NO_2 estimates when instrumenting with the "wind-from-plant" dummy under alternative distance and angular cutoffs. In column (1), we define "downwind" as any sub-daily interval with wind within $\pm 45°$ of the bearing from the 25 km-distant plant to the site. The second stage yields a coefficient of 0.0181 (SE = 0.0079), implying that a 10 ppb NO_2 increase raises accident probability by 136 %, and the first-stage F ≈ 339 confirms strong relevance. Expanding the plant-site radius to 50 km (column 2) attenuates the point estimate slightly to 0.0152 (SE = 0.0073)—still significant at the 5 % level—and corresponds to a 118 % increase per 10 ppb.[36] This mirrors our expectation that pollution from more distant emitters has a slightly smaller impact but remains a valid shock and provides supportive evidence that our results are unlikely to be driven by locally omitted activity variables.

In columns (3) and (4), we relax the wind-direction bin to $\pm 60°$ and $\pm 90°$ (holding the 25 km radius), which further smooths the instrument but preserves its strength. Column (3) reports a coefficient of 0.0107 (SE = 0.0050), an 81 % effect, while column (4) shows 0.0112 (SE = 0.0058), an 85 % effect. Although precision declines marginally as the angular window widens, all four specifications continue to reject the null at conventional levels, demonstrating that our wind-from-plant IV is robust to alternative definitions of "downwind". Overall our 2SLS estimates are similar to our OLS coefficients (higher for the "wind-from-plant" instrument due to the resulting higher concentration), 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.

Building on the single-pollutant wind-from-plant IV, column (5) of Table 4 implements a multi-pollutant two-stage least-squares regression that instruments simultaneously for NO_2 and $PM_{2.5}$ using their respective plant-wind shocks. Crucially, the two first-stage equations remain strong and well-identified for both pollutants (each F-statistic >180), demonstrating the ability to identify each effect separately as different plants dominate each instrument. These joint-IV second stage estimates

[34] The results are robust to using different cutoffs for the radius.

[35] 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 Eq. (2), and when we combine the lagged instruments with the IV of the pollution levels measured at stations within a radius of 5–10 km. We further test for the exogeneity of our instruments using the Sargan-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.

[36] The results are robust to the use of other specifications of the distance cutoff and are available from the authors.

Table 4
Polluting plants instrumental variable.

Distance to plant Degree bin	25 km 45° (1)	50 km 45° (2)	25 km 60° (3)	25 km 90° (4)	25 km 45° (5)
NO_2	0.0181** (0.0079)	0.0152** (0.0073)	0.0107** (0.0050)	0.0112* (0.0058)	0.0191** (0.0093)
$PM_{2.5}$					0.0094 (0.0103)
F-statistic (NO_2 1st Stage)	339.3	354.3	407.9	371.1	181.7
F-statistic ($PM_{2.5}$ 1st Stage)					210.2
10 ppb Increase on Prob. of Accident	136 %	118 %	81 %	85 %	118 %
Construction Sites	5080	5444	5080	5080	3381
Observations	1,989,030	2,151,021	1,989,030	1,989,030	1,153,421

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 1000 for ease of reading. Time-fixed effects include the dummy variables for the year, month, and day of the week. Weather variables include wind, humidity percentage, temperature rate, and equivalent squared variables. The instruments are dummies indicating whether the wind blows from the nearest polluting plant to the monitor interacted with a dummy for each plant. NO_2 and $PM_{2.5}$ readings are restricted to within 1 km from the site. Standard errors are robust, adjusted for clusters by polluting plant, and appear in parentheses. The effect of 10-ppb is compared to the average accident rate in each regression. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

mirror our earlier single-pollutant IVs for NO_2 while confirming that short-term $PM_{2.5}$ fluctuations do not independently affect accident risk. Consistent with Table 2, these IV results lend additional support to the interpretation that NO_2 exposure causally affects construction-site accidents.

5.2. Non-linear effect results

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 3, we focus on high pollution levels and present the results where we use specifications including the dummy variables for moderate and high pollution levels (between the 95th and 99th percentiles and above the 99th percentile of NO_2 levels, respectively), as specified in Eq. (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 0.000159

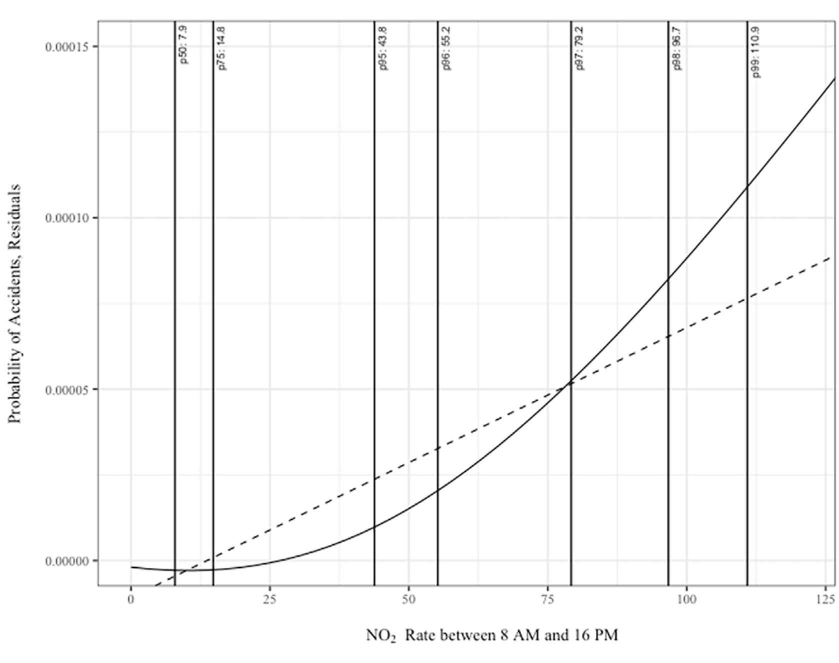

Fig. 5. Semi-parametric estimation of the effect of NO_2 on the probability of an accident, distance limited to 1 km. *Notes*: The continuous line represents the semi-parametric estimation of the connection between NO_2 levels at the closest measuring station and the probability of an accident at a construction site. The dashed line represents the linear connection.

Table 5
Robustness of the effect of NO_2 on the probability of a construction accident. Varying monitor distance, 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*** (0.0010)	0.0018*** (0.0006)	0.0009* (0.0005)	0.0005 (0.0005)	0.0039*** (0.0014)			0.0041*** (0.0013)
AQI						0.0042** (0.0019)	0.0042** (0.0016)	
AQI (excluding NO_2)								−0.0008 (0.0007)
Wald F-statistic						38.8	19.9	
Reduced Form						0.0038* (0.0020)	0.0035** (0.0014)	
10 ppb Increase on Prob. of Accident	25 %	15 %	8 %	4 %	32 %	27 %	28 %	36 %
Construction Sites	5583	10,119	12,765	18,896	5433	4792	5025	5018
Observations	2,189,124	4,119,202	5,211,326	7,803,472	1,185,624	1,228,292	1,266,995	1,261,140

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 1000 for ease of reading. All regressions include time, weather, and site-fixed effects. Time-fixed effects contain the dummy variables for the year, month, and day of the week. Weather variables include 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 the relevant pollutant's pollution monitor, and appear in parentheses. The effect of 10 ppb is compared to the average accident rate in each regression.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

percentage points (SE = 0.0001076) in the probability of an accident, which translates to an increase of 138 %, significant at the 1 % level. 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 % or 4.06 more accidents per 100,000 workers yearly, statistically significant at a 1 % level.

In Fig. 5, we present the results of our semiparametric specification described in Eq. (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 Fig. 5, the marginal effect of an increase in pollution levels becomes larger than our OLS estimate around the 95th percentile and becomes 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.[37]

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 5, we present evidence that the effect size and significance are reduced when we allow for measurements of pollution from monitoring stations that are farther away from the construction site. In our main analysis, column (1), we restrict our observations to construction sites where the closest monitoring station for pollution levels is up to 1 km away. In columns (2–4), we increase this range to 1.5, 2, and 5 km, respectively. We observe a continuous decrease in both the effect size and significance levels. This suggests that the effect is indeed related to pollution levels present in the close vicinity of the construction site rather than 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 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

[37] The results are consistent and remain significant when we use NO instead of NO_2 as our measure of pollution and are presented in Appendix Table A5. 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).

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 the 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 measures NO_2 alongside the other major pollutants we observe ($PM_{2.5}$, O_3, and SO_2).

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 5, 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 for the other pollutants.

We next address concerns about potential systematic under-reporting. Under-reporting of accidents would only bias our estimates if pollution levels varied with reporting behavior. Using the Kav LaOved accidents, we alleviate this concern. As these cases represent accidents that were not initially reported, if pollution systematically influences whether accidents are reported, we would expect the pollution-accident relationship to differ when including versus excluding these alternatively reported cases.[38] Our estimates remain unchanged when excluding Kav LaOved accidents. This robustness provides suggestive evidence that pollution levels do not affect reporting decisions.

Next, we attempt to mitigate concerns regarding the co-determination of pollution levels and accidents potentially resulting from pollution from construction sites to the closest monitoring station. As the wind's direction can determine the spatial distribution of pollutants, we run our baseline model in Eq. (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 co-determination of other factors generating pollution at the site and increasing the probability of an accident simultaneously. In column (5) of Table 5, we report the results of this specific exercise and compare them to our main specification. The results remain robust in size and significance.[39]

In column (8) of Table 5, 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, consistent with our findings in Table 2 and column (5) of Table 4 which also show that both the magnitude and significance of the effect of NO_2 are robust to the addition of additional pollutants to the regression. 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. While we cluster the standard errors by monitoring stations in our analysis to account for this issue, in Appendix Table A6, we further show that our results remain robust when implementing Conley's spatial standard errors. We report Conley-adjusted standard errors, with various distance cutoff parameters, for our main Table 3 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). Furthermore, to examine the potential magnitude of this issue in our case, in Appendix Table A6, we also report our main results when clustering the standard errors by construction sites rather than monitoring stations. All our results remain statistically significant for these cases.

Finally, we conducted two placebo tests. In the first test, we substituted our same-day pollution estimate with the pollution levels from the subsequent two days. The results indicate that the coefficient decreases and becomes statistically 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 suggests that while pollution is often regarded as highly temporally correlated, NO_2 displays considerable temporal variability, providing 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 high frequency pollution measurements to accurately capture its effects.

In our second placebo test, we replace the same-day pollution estimate with pollution level from the lags and leads of 1–12 months (i.e., assigning each observation the level of NO_2 on the same day 1 to 12 months before or after). The results of this analysis are presented in Appendix Figure A4. Among the estimates, only our same-day pollution estimate is significant at the 1 % significance level; and only 4.17 % of the other estimates are significant at the 5 % level. These findings further reinforce the validity of our results, supporting their non-spurious nature.

7. Mechanisms 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 workweek, providing suggestive evidence that "weekend fatigue" might be a contributing factor.

According to Fig. 2 Panel A, our data display 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 Eq. (1), we can examine whether there is a differential effect of pollution on the probability of an accident depending on the day of the week. As we can see in column (8) of Table 6, 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 reduced attentiveness and increased distractibility at the start of the workweek. Workers returning from the weekend break may experience lower cognitive awareness, making them particularly vulnerable to NO_2's cognitive impairments. This result suggests that a potential channel for pollution's effect on accidents may be related to the heightened vulnerability when baseline attention is already compromised, suggesting that the 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 of a high cognitive load or physical strain that put workers at greater risk.[40] High levels

[38] Potential existence of under-reporting due to pollution, in this scenario, would result in a lower estimated effect in our pollution-accident relationship.

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

[40] 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.

Table 6
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*** (0.0010)	0.0069*** (0.0016)	0.0026*** (0.0009)	0.0047*** (0.0015)	0.0026*** (0.0010)	0.0052** (0.0024)	0.0031** (0.0013)	NO_2	0.0083*** (0.0018)
								Mon. × NO_2	−0.0056*** (0.0011)
								Tue. × NO_2	−0.0067*** (0.0016)
								Wed. × NO_2	−0.0060*** (0.0019)
								Thu. × NO_2	−0.0068*** (0.0011)
10 ppb Increase on Prob. of Accident	25 %	57 %	19 %	27 %	23 %	61 %	21 %		
Construction Sites	5583	5317	5520	5054	5500	5226	5541		5583
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 1000 for ease of reading. All regressions include time, weather, and site-fixed effects. Time-fixed effects contain the dummy variables for the year, month, and day of the week. Weather variables include 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 in the baseline linear model with controls presented in Eq. (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 NO_2 pollution monitor, and appear in parentheses. The effect of 10 ppb is compared to the average accident rate in each regression. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

of pollution might exacerbate the effects of these already difficult conditions.[41]

As seen in columns (2–7) of Table 6, pollution plays an increased role when wind strength, temperature level, and/or humidity level are above the 75th percentile, in contrast to the mild conditions where levels are below the 75th percentile.[42] These findings overall 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. However, 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; Park et al., 2021). Our study offers unique advantages compared to those focusing primarily on $PM_{2.5}$. Considering NO_2 is its precursor, our analysis captures a more precise temporal pollution estimation (Deryugina et al., 2019). For example, including daytime $PM_{2.5}$ in our main instrumental variable estimates from Table 3, columns (3–4) yields comparable significant estimates for NO_2 while showing no effect for $PM_{2.5}$.[43]

We further examine the effects of these determinants in our setting, taking advantage of the high density and spatial distribution of air pollution monitoring stations in our sample. We use these 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. In Appendix Table A3, we show that when controlling for only limited specifications, our results are also significant for the effect of $PM_{2.5}$ on workplace accidents. The 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 $PM_{2.5}$ are reduced in size and significance and are no longer present.[44]

In light of these results, caution should be exercised when conducting similar analyses. Omitting relevant time and weather variables and,

[41] See also Graff Zivin et al. (2023), which demonstrate the compounding effects of air pollution and influenza.

[42] This analysis should be interpreted as suggestive evidence, as the interactions between the weather variables and NO_2 could influence the incidence of accidents through other unobserved channels, amplify the incidence of pollution or affect the measurement error in other variables. Even though our 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, the causal interpretation of these results—as the interaction effect of stress and NO_2—should be drawn with caution.

[43] Comparable results are found when examining the dynamic relationship between NO_2 and Ozone (O_3), as only the effects of NO_2 are significant when both pollutants are included in the regression. Additionally, we find that the effect of NO_2 on accidents remains stable in both the summer and the winter months, providing further support for the robustness of the effect of NO_2 against multicollinearity threats related to O_3 levels, as O_3 levels are much higher during the summer months.

[44] In Appendix Table A7, we present similar patterns related to the effect of temperature, although we caution that this result might be more sensitive to specific location-based weather condition variations and adaptations to them.

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.[45]

The difference in the effects we find for the different pollutants and temperature in Table 2 and Appendix Tables A3 and A7, might be partially explained by a lack of spatial variation in 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 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 in 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, provide 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 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, 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.[46]

7.1. Physiological mechanisms

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. The difference could be partly explained by the differing physiological mechanisms of the two pollutants.

NO_2 is a potent respiratory irritant that can trigger acute symptoms even at relatively low ambient concentrations. Inhaled NO_2 rapidly irritates the mucous membranes of the nose, throat, and lungs, provoking coughing, wheezing, and difficulty breathing on the same day of exposure (U.S. Environmental Protection Agency, 2024). The acute respiratory impairment that can be induced by exposure to NO_2 can reduce pulmonary oxygen exchange and lead to transient hypoxemia or shortness of breath. In turn, the body may experience mild cardiovascular stress as it struggles to compensate—for example, high NO_2 exposures interfere with blood oxygenation and have been reported to cause headaches, dizziness, and fatigue due to limited oxygen transport (methemoglobinemia). Even at non-extreme ambient levels, NO_2's irritant effect can produce "nonspecific" malaise symptoms in healthy adults—such as a slight cough, nausea, or tiredness—within hours of exposure (Agency for Toxic Substances and Disease Registry, 2014; Jiang et al., 2019). Beyond the obvious pulmonary effects, same-day NO_2 exposure may also degrade neurocognitive functioning and alertness, which are critical for safety (Allen et al., 2017; Gignac et al., 2022). In a heavy outdoor work setting like construction, these acute respiratory, circulatory and cognitive responses to NO_2 could directly impair a worker's physical performance (by reducing endurance and muscle oxygenation), balance or coordination (via dizziness or lightheadedness), and attention and decision making thereby increasing the risk of accidents on the same day.

$PM_{2.5}$'s health effects, though serious, might be less acutely disruptive in the immediate term and rather unfold more gradually via inflammation and cardiovascular stress that build over time through deposited particles in the alveoli (Mainka and Żak, 2022; Mebrahtu et al., 2023; Pryor et al., 2022). This might be particularly the case in the context of our study, which focuses on subclinical impacts on working-age individuals. In the short span of a single workday, for a typical healthy worker, those processes might not progress far enough to impair a worker's reflexes or decision-making to a dangerous degree. Another factor is that $PM_{2.5}$, unlike NO_2, produces less sensory acute discomfort for the average person. Fine particles are largely invisible and odorless; they do not sting the eyes or throat in the way NO_2 (a pungent gas) can at high concentrations. As a result, workers might not experience the kind of sudden coughing or breathlessness that would directly slow them down or distract them on the job. Additionally, cognitive effects of $PM_{2.5}$ on the same day might be milder or affect functions which could be less relevant to accident proneness (Wang et al., 2021; Sakhvidi et al., 2022; Allen et al., 2017). Taken together, same-day exposure to NO_2 might have a comparatively strong, or more relevant, impact on the physiological and cognitive faculties that govern immediate safety in our setting. While translating these differences in physiological mechanisms to the effect of each pollutant on human activity is suggestive and requires further research, new findings, such as the findings of our study, can contribute to our understanding of the differentiated impact of each pollutant.

Importantly, our focus on NO_2 does not imply that other pollutants are irrelevant for workplace safety in all contexts. Rather, our findings highlight NO_2 as a particularly important pollutant to monitor for three reasons. First, we find that NO_2 has a strong and robust effect on construction accidents. Second, its high spatial and temporal variability makes it a feasible target for real-time safety interventions. Third, the severe physiological mechanisms through which NO_2 affects worker performance make it especially relevant for accident prevention in high-risk work environments. Thus, in a resource-constrained setting where monitoring and reacting to all pollutants may not be feasible, this suggests that policy might prefer favoring NO_2 over others.

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

[45] While examining these other determinants is not the main focus of our paper, for the sake of robustness, in Appendix Table A6, 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.

[46] Sager and Singer (2024) also demonstrate the importance of using a smaller geographical unit of measure in avoiding biased estimates of pollution exposure.

the Central Bureau of Statistics on the costs to the government due to construction accidents and construction site closures. Then, we run a cost-benefit 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 % 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, 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:

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

where $Pr(Accident|NO_2)$ is the average probability of an accident for the day given local NO_2 levels, $Costs_{Accident\ Insurance}$ is the costs of insurance paid out per injury by the government, and $LostTaxRevenue$ represents the tax revenue forfeited due to the worker's inability to earn taxable income following the accident. 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[47] 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 ($P_2 = 5372$ million NIS)[48] multiplied by the difference between the average life expectancy ($Age^e = 83$) and the average age of the injury[49] ($\bar{Age} = 39$). This sum is then multiplied by the percentage of accidents that are a direct cause of construction site accidents[50] ($p_{con} = 10.7$ %). Finally, this sum is divided by the number of construction injuries the agency pays for in a year (6892). This calculation yields a total cost of approximately 3,681,000 NIS per injury. Formally this calculation is given by:

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

Similarly, we estimate forfeited tax revenue by calculating the average tax payments lost per year multiplied by the difference between the retirement age and the average age of injury, yielding approximately 850,000 NIS per accident (imputations based on data from the NII and Israeli Tax Authority). Plugging the total costs per injury into Eq. (7), we can estimate that the expected cost savings to the government from closing the construction site for the day is $P_{Accident} \times 4.531$ 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.[51] 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 non-linearities in the connection between pollution levels and the probability of an accident, Fig. 6 presents a nonparametric estimation similar to its approach to Eq. (6). By implementing such a strategy, we predict the probability of an accident more accurately across different pollution levels to suggest a more precise monetary subsidy based on pollution levels. Table 7 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.[52] 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 1322 NIS; thus, the maximum subsidy amount 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 2635 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.[53] 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 the awareness of contractors and workers, investments in safety measures, training, safety standards, scaffolding, individual pollution sensors, respirators, and other relevant equipment.

8.1. High-pollution days: annual severe-accident burden and fiscal impact

To gauge the real-world scale of NO_2-driven severe accidents, we focus on days above the 95th percentile of NO_2 exposure—this threshold corresponds to the EPA's definition of "non-clean" air (i.e. the lower bound of the "Moderate" category). By isolating these extreme-pollution days, and using back-of-the-envelope calculations, we can ask: how many *additional* construction-site severe accidents do they generate each year, and what share of the total burden do they represent?

Over our 2017–2019 sample we observe $10,016,000$ construction-site working-day observations and 1164 reported severe accidents. Hence

$$\frac{1164}{3} \approx 388$$

construction-site severe accidents *per year*, which we use to benchmark percentage shares.

[47] 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.

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

[49] 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).

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

[51] A report by an appraiser office finds an estimated average loss of 9000 NIS for a relatively large construction site being closed for a period of 24 hours (accessed July 19th, 2022).

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

[53] Because this cost–benefit analysis focuses on direct fiscal costs and benefits to the government, we exclude non-pecuniary welfare losses from post-injury quality-of-life changes. For reference, one can estimate these losses via a quality-adjusted life-year (QALY) approach: using a willingness-to-pay per QALY in Israel of 390,000 NIS (inflation-adjusted; Shmueli (2009)) and an estimated loss of $\Delta QALY = 0.1$ per severe injury (Raich et al., 2023), the implied welfare cost is 39,000 NIS per injury. Although this adds a non-negligible almost 1 % to the direct insurance-and-tax costs, it would not materially alter our main conclusions.

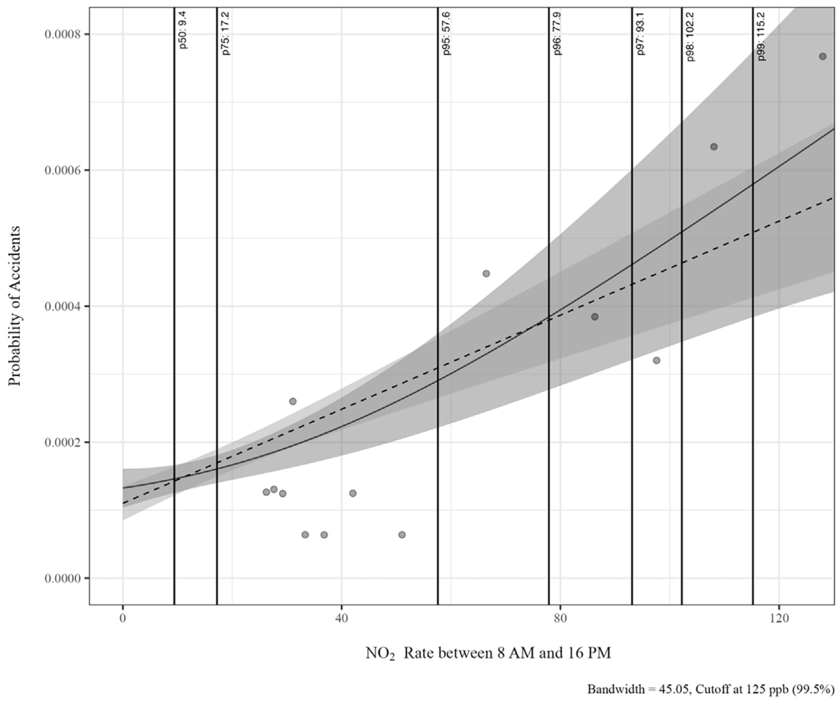

Fig. 6. Nonparametric estimation of the effect of NO_2 on the probability of an accident, excluding weekends and distance limited to 1 km. *Notes*: The continuous line represents the non-parametric estimation of the connection between NO_2 levels at the closest measuring station and the probability of an accident at a construction site. The dashed line represents the linear 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 85th percentile. The dark shaded area represents the 95 % confidence intervals based on the robust and clustered standard errors that relate to the linear model, while the light gray area represents the 95 % bootstrap confidence intervals related to the non-parametric estimation.

Table 7
Cost benefit analysis of pollution levels and subsidy amounts.

Nitrogen dioxide level	Percentile	Probability of an accident	Subsidy (NIS)	95 % Confidence intervals	
5.4	25 %	0.000140	633	530	737
9.4	50 %	0.000144	651	558	748
17.2	75 %	0.000159	721	629	811
30.2	91 %	0.000193	873	732	1013
32.1	92 %	0.000201	910	754	1064
34.8	93 %	0.000209	947	778	1116
39.0	94 %	0.000218	988	803	1184
45.6	95 %	0.000247	1121	883	1356
57.6	96 %	0.000291	1322	1005	1636
77.9	97 %	0.000394	1783	1280	2287
93.1	98 %	0.000464	2101	1463	2741
102.2	99 %	0.000507	2299	1570	3027
115.2	100 %	0.000582	2635	1744	3526

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 4.531 million NIS, and the subsidy amount is calculated by multiplying this amount by the probability of an accident corresponding to each NO_2 level according to our nonparametric estimate; see paper for details. The 95 % confidence intervals are calculated using a bootstrap estimation method.

Let

$$\bar{p}_{\text{clean}} = \frac{1}{94}\sum_{p=1}^{94} \Pr\left(\text{severe accident} \mid NO_2 = \text{p-th percentile}\right) \approx 0.0001516$$

be the *baseline* severe-accident probability on truly "clean" days (below the 95th percentile). We have roughly

$$\frac{10,016,000}{3} \approx 3,338,667$$

site-days *per calendar year*, and each integer percentile above 95 occupies 1 % of days, or

$$0.01 \times 3,338,667 \approx 33,387$$

site-days annually. Therefore, for each high-pollution percentile $p \geq 95$, the extra severe accidents per year are

$$A_p = \left[\Pr(\text{severe accident} \mid p) - \bar{p}_{\text{clean}}\right] \times 33,387.$$

Using our nonparametric estimates $\Pr(\text{severe accident} \mid p)$ from Table 7 and summing A_p across $p = 95, \ldots, 100$ yields approximately 53 extra severe accidents per year, or about 14 % of the roughly 388 annual severe-accident cases.[54] At an average insurance payout of 4.531 million NIS per severe accident, these high-pollution-day events alone imply ∼240 million NIS in excess annual payouts to the National Insurance Institute. This subsection thus demonstrates that while days with NO_2 above the EPA "clean" cutoff are relatively rare, they account for a disproportionately large share of construction-site severe accidents and impose a material fiscal burden.

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 instrumental variable analyses and robustness checks. We did 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 under conditions in which 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 involving 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, using our estimates, calculates pollution thresholds at which it could be beneficial for the government to subsidize temporary construction-site closures.

Declaration of competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data for this article can be found online at doi:10.1016/j.jpubeco.2025.105472.

Data availability

Data will be made available upon request.

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[54] In Appendix Table A10 we present the detailed calculation for each percentile.

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