Wildfire Smoke and Road Accidents: Evidence from Alberta

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Abstract

This paper examines how wildfire smoke exposure affects road safety in Alberta. Combining satellite-based smoke plume data with municipality-day accident records from 2016 to 2022, I find that accident incidents rise on low- and medium-smoke days but fall sharply on heavy-smoke days. Traffic volume data show that vehicle counts remain unchanged when smoke is light yet decline substantially under heavy smoke, indicating that people avoid driving only when conditions are visibly severe. These patterns suggest that on low-smoke days, drivers continue their usual travel but may experience reduced cognitive performance, leading to more accidents even though they do not perceive a risk. The results highlight an overlooked behavioral cost of wildfire smoke exposure and underscore the need for public awareness that smoke can impair cognition and driving safety even when it is not readily perceptible.

Key Words: Wildfire, Smoke, Accidents, Cognitive, Avoidance

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1 Introduction

Wildfires have intensified in scale and impact over the past two decades, with 2021, 2024, and 2023 ranking as the third and worst years globally, respectively[1]. These events have more than doubled the area of tree cover burned worldwide, extending the duration and intensity of smoke plumes compared to two decades ago (Potapov et al., 2025). Wildfires emit a broad spectrum of pollutants, including greenhouse gases such as carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O). They also release photochemically reactive compounds — carbon monoxide (CO), nonmethane volatile organic compounds (NMVOC), and nitrogen oxides (NO_x) — along with fine and coarse particulate matter (PM) (Urbanski et al., 2008). In 2023, Canadian wildfires emitted approximately 647 TgC of carbon, an amount comparable to the annual fossil fuel emissions of major economies; only India, China, and the United States released more carbon that year (Byrne et al., 2024). On May 16, 2023, the $PM_{2.5}$ concentration in southeast Calgary reached 558 $\mu g/m^3$, nearly 93% of Bangladesh's peak level that year.[2] Toxicological evidence further indicates that particulate matter from wildfire smoke is more harmful than equivalent doses of urban or industrial pollution (Aguilera et al., 2021).

Wildfire smoke thus represents an increasingly important, widespread, and severe form of air pollution with direct implications for human health, productivity, and behavior. A growing literature in economics has examined how air pollution influences a wide range of outcomes: labor productivity and labor supply (Hanna and Oliva, 2015; Zivin and Neidell, 2012; Borgschulte et al., 2022; Hoffmann and Rud, 2024), cognitive performance and decision quality (Ebenstein et al., 2016; Chang et al., 2019), health and mortality (Dockery and Pope, 1994; Miller et al., 2024; Grant and Runkle, 2022), and even social behaviors such as aggression and crime (Herrnstadt et al., 2016; Bondy et al., 2020; Burkhardt et al., 2019; Singh and Visaria, 2021). Yet, the behavioral and safety consequences of wildfire smoke —

[1]See https://www.wri.org/insights/global-trends-forest-fires.

[2]Bangladesh was the most polluted country in 2023.

especially in routine activities like driving — remain largely unexplored. This paper examines how exposure to wildfire smoke influences road safety, focusing on the incidence of traffic accidents in Alberta, Canada. I combine satellite-based data on smoke plumes with detailed municipality-day accident records from 2016 to 2022 to estimate the impact of smoke exposure on traffic accidents.

The empirical strategy exploits within-municipality, within-month day-to-day variation in the intensity of smoke exposure. Because wildfire smoke can travel long distances and fluctuate sharply over space and time, its arrival in a given area is plausibly unrelated to local driving conditions or behaviors. I merge satellite-based smoke plume data from NOAA's Hazard Mapping System with administrative accident records from the Government of Alberta and control for local weather, seasonality, and time-varying municipality-specific factors using high-dimensional fixed-effects. This design isolates the short-run effect of smoke exposure on accident rates while minimizing confounding from correlated local shocks.

The analysis reveals a striking nonlinear relationship. Accident incidents increase on low- and medium-smoke days but fall sharply on high-smoke days. Complementary traffic flow data from the city of Calgary show that vehicle volumes remain unchanged when smoke is light yet decline substantially under heavy smoke. These patterns suggest that drivers avoid travel only when smoke is severe. On days with lower levels of smoke — when perceived risk remain largely unaffected — drivers continue normal routines but may experience subtle cognitive impairments that elevate accident risk. Consistent with this interpretation, the effects are concentrated in urban areas, on weekdays, and in the pre-COVID period — settings where travel is less easily avoided. The findings indicate that wildfire smoke can affect safety even when individuals do not consciously perceive the hazard.

This paper contributes to several strands of literature. First, it adds to the growing body of work examining how air pollution affects human behavior and decision-making. Previous studies have shown that pollution exposure reduces cognitive performance (Ebenstein et al., 2016; Chang et al., 2019), worker productivity (Hanna and Oliva, 2015; Zivin and Neidell, 2012; Borgschulte et al., 2022), and health (Miller et al., 2024). This paper links those cognitive and productivity effects to tangible safety outcomes that carry social and economic costs, showing that impaired cognition can manifest in increased accident risk. Second, it contributes to the literature on air pollution and road safety. Prior studies have documented that pollution can influence accident frequency and severity, though findings are mixed: some report increases in the number of crashes (Sager, 2019; Wang et al., 2023; Shi et al., 2022; Baryshnikova and Wesselbaum, 2023; Burton and Roach, 2023), while others observe declines in severe accidents, consistent with greater caution or avoidance (Shr et al., 2023; Deng et al., 2024). By distinguishing between low- and high-smoke days, this paper helps reconcile these divergent results — showing that when pollution is salient, behavioral avoidance dominates, whereas when it is subtle, cognitive impairment drives more accidents.

Third, the study contributes to the emerging economics literature on wildfire smoke as a unique form of pollution. Recent work has examined its effects on health (Miller et al., 2024; Grant and Runkle, 2022), labor market outcomes (Borgschulte et al., 2022), and productivity (Cvijanovic et al., 2024), as well as on school performance and cognitive outcomes (Wen and Burke, 2022). Wildfires generate short-lived yet intense exposure episodes that are spatially widespread and increasingly frequent. They also differ chemically from urban pollution, with particulate matter that is more toxic and cognitively disruptive. By documenting the behavioral and safety implications of such exposure, this paper highlights an underrecognized welfare cost of wildfire smoke — one that operates through impaired cognition and reduced public safety rather than through health or labor market channels. The results also shed light on the limits of behavioral adaptation to environmental risks that are not readily perceived, underscoring the importance of risk communication and public awareness in mitigating the social costs of pollution exposure.

Finally, the results have implications for both policy and public awareness. Because even light smoke can increase accident risk without being readily perceived, public advisories might usefully emphasize that smoke can impair cognition and decision-making at lower levels of exposure than most people realize. Encouraging work-from-home arrangements and travel reduction during smoky periods could improve both health and safety outcomes.

The remainder of the paper proceeds as follows. Section 2 describes the data sources and variable construction. Section 3 presents a conceptual framework linking smoke exposure, cognition, and avoidance behavior. Section 4 outlines the empirical identification strategy. Section 5 reports the main results and heterogeneity analyses, and Section 6 explores mechanisms. Section 7 concludes.

2 Data

This study combines three primary datasets to examine the relationship between wildfire smoke and road accidents in Alberta. The first is the universe of police-reported traffic accidents from 2016 to 2022, obtained from the Government of Alberta. These administrative records provide detailed information on each incident, including the date, location, severity (fatal, injury, property damage), number of vehicles involved, and driver demographics. I aggregate these records to the municipality–day level to construct total daily accident counts as well as disaggregated counts by severity.

The second dataset measures wildfire smoke exposure. I use satellite-based data from NOAA's Hazard Mapping System (HMS), which detects and classifies visible smoke plumes each day across North America into light, medium, and heavy density categories. Smoke polygons are merged to Alberta's municipal boundaries using spatial shapefiles, producing municipality–day indicators for smoke presence and intensity. To validate this measure and control for other air quality factors, I supplement the HMS data with hourly ambient air pollution readings from Environment and Climate Change Canada (ECCC), including $PM_{2.5}$, temperature, precipitation, and visibility. Hourly observations are averaged to the daily level, and I compute inverse distance-weighted averages from monitoring stations within 100 kilometers of each municipality centroid following Borgschulte et al. (2022).

Finally, to assess avoidance behavior, I use camera-based traffic counts from the City of Calgary (2022 - 2024). These daily traffic volumes, aggregated across major intersections, serve as a proxy for the number of vehicles on the road and allow me to test whether heavy smoke discourages travel.

All datasets are merged at the municipality–day level using consistent spatial identifiers and restricted to the wildfire season (May - October), when smoke exposure is most frequent. The resulting dataset contains information on road accidents, smoke plume coverage, ambient air pollution, and weather for 2016 - 2022, supplemented by traffic volume data for Calgary. Table 1 reports summary statistics.

Table 1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Accidents	413,448	2.187	16.710	0	940
Smoke (any)	413,448	0.319	0.466	0	1
Smoke (light)	413,448	0.254	0.435	0	1
Smoke (medium)	413,448	0.009	0.092	0	1
Smoke (heavy)	413,448	0.056	0.230	0	1
Smoke coverage (%)	413,448	30.676	45.776	0	100
$PM_{2.5}$ ($\mu g/m^3$)	387,502	7.579	11.686	0	1102.489
Temperature (°C)	413,300	12.481	6.240	-16.994	31.542
Precipitation (mm)	413,448	1.171	4.996	0	660.624
Visibility (km)	359,209	23.079	7.913	0.365	57.621

Notes: Observations are at the municipality–day level for May–October, 2016–2022.

3 Conceptual Framework

Wildfire smoke can affect accident counts through two competing mechanisms: a direct effect on driver cognition and an indirect effect through changes in driving behavior. Let W denote smoke exposure, C cognitive performance, and N the number of vehicles on the road. The probability that a representative driver reaches home safely is $\Phi(C(W, Z), N(W, Z))$, where Z includes weather and other controls. The total number of accidents can be written as

$A = (1 - \Phi)\, N(W, Z)$. Differentiating with respect to W yields:

$$\frac{dA}{dW} = \underbrace{-\frac{\partial \Phi}{\partial C}\,\frac{\partial C}{\partial W}\, N(W, Z)}_{\text{Cognitive impairment (direct effect)}} + \underbrace{\left[-\frac{\partial \Phi}{\partial N}\,\frac{\partial N}{\partial W}\, N(W, Z) + (1 - \Phi)\,\frac{dN(W, Z)}{dW}\right]}_{\text{Avoidance behavior (indirect effect)}}.$$

If smoke exposure reduces cognitive performance ($\frac{\partial C}{\partial W} < 0$) and discourages travel ($\frac{\partial N}{\partial W} < 0$), the first term increases accidents while the second reduces them. The net effect can thus be positive or negative depending on which effect dominates. This framework motivates the empirical design below, which estimates reduced-form responses to smoke exposure and tests for nonlinearity across smoke intensity bins.

4 Empirical Strategy

Consistent with the conceptual framework, the empirical objective is to estimate how wildfire smoke exposure (W) affects the number of road accidents (A) at the municipality–day level, controlling for weather and time-varying local factors. Specifically, I estimate the semi-elasticity of accident counts with respect to smoke exposure, leveraging day-to-day variation in smoke intensity within each municipality and month, while controlling for year fixed effects. Because wildfire smoke can drift long distances and fluctuate sharply over space and time, its daily presence in a municipality within a given month is plausibly exogenous to local driving conditions.

Formally, I estimate the following equation:

$$\text{Accidents}_{idmy} = \exp\left(\alpha + \beta_1\, \text{Smoke}_{idmy} + \gamma' X_{idmy} + \lambda_{im} + \delta_{iy}\right) \epsilon_{idmy}, \tag{1}$$

where Accidents_{idmy} is the number of police-reported traffic accidents in municipality i on day d of month m and year y. Smoke_{idmy} is the main variable of interest, indicating whether a municipality is covered by wildfire smoke on a given day.[3] X_{idmy} is a vector of weather

[3]A municipality is considered covered by smoke if more than 50% of its land area lies within a smoke

controls including daily temperature, precipitation, and visibility. λ_{im} are municipality-by-month fixed effects that capture time-invariant seasonal driving patterns specific to each municipality (for example, differences between summer and fall driving habits), while δ_{iy} are municipality-by-year fixed effects that control for annual local shocks such as changes in population, infrastructure, or enforcement intensity. The idiosyncratic error term ϵ_{idmy} is assumed to have mean zero conditional on the included covariates and fixed effects.

The coefficient of interest, β_1, measures the semi-elasticity of accident counts with respect to smoke exposure. It can be interpreted as the percentage change in the expected number of accidents when a municipality is covered by smoke compared to when it is not, holding other factors constant. Mathematically, the marginal effect of smoke on expected accidents is:

$$\frac{\partial \mathbb{E}[\text{Accidents}_{idmy}]}{\partial \text{Smoke}_{idmy}} = \beta_1 \cdot \mathbb{E}[\text{Accidents}_{idmy}], \quad (2)$$

so $(\exp(\beta_1) - 1) \times 100$ gives the percentage change in expected accident counts associated with smoke coverage.

The identification strategy exploits daily variation in smoke exposure that is orthogonal to local determinants of road safety. Wildfire smoke originates far from most municipalities in Alberta and is transported by prevailing winds, creating spatially and temporally idiosyncratic variation in pollution intensity. This design mitigates standard endogeneity concerns that arise when pollution is locally generated, for example, by traffic congestion or industrial activity, which could correlate with accident risk. Because wildfire smoke dispersion depends primarily on meteorological factors, and not on local driving behavior, its short-run arrival in a given area is plausibly exogenous to traffic conditions.[4]

Nonetheless, residual confounding could arise if smoke exposure coincides with unobserved factors that also affect accident risk (e.g., changes in sunlight or temperature). I therefore include comprehensive weather controls and absorb municipality-by-month and

plume polygon, based on NOAA HMS data.

[4]Following Borgschulte et al. (2022) and Miller et al. (2024), who similarly exploit long-distance smoke transport as an exogenous pollution source.

municipality-by-year fixed effects to isolate the within-municipality, day-to-day variation in smoke intensity. Standard errors are clustered at the municipality level, allowing for arbitrary spatial correlation in unobservable. The dependent variable, the number of daily accidents, is count data with many zeros and substantial heteroskedasticity. Ordinary least squares (OLS) on log-transformed counts would require dropping zero observations and would be inconsistent under heteroskedasticity. Instead, I estimate equation (1) using the Poisson Pseudo-Maximum Likelihood (PPML) estimator, which provides consistent estimates of semi-elasticities in nonlinear count models without requiring equality of the mean and variance (Wooldridge, 2009). PPML also accommodates heteroskedasticity and allows the inclusion of high-dimensional fixed effects via iterative algorithms, making it well suited to this setting.

To test the theoretical prediction that the net effect of smoke depends on the balance between cognitive impairment and avoidance behavior, I estimate equation (1) with separate indicators for light, medium and heavy smoke:

$$\begin{aligned}\text{Accidents}_{idmy} = \exp\big(\alpha + \beta_L\,\text{LightSmoke}_{idmy} + \beta_M\,\text{MediumSmoke}_{idmy} + \beta_H\,\text{HeavySmoke}_{idmy} \\ + \gamma' X_{idmy} + \lambda_{im} + \delta_{iy}\big)\,\epsilon_{idmy}.\end{aligned} \tag{3}$$

Comparing β_L, β_M, and β_H allows me to assess whether there are non-linear effects in the impact of smoke on traffic accidents.

Throughout, the coefficients are interpreted as percentage changes relative to smoke-free days within the same municipality and month. For example, $\beta_L = 0.02$ implies that light smoke increases daily accidents by approximately 2%, holding local conditions constant. Because wildfire smoke is transitory and spatially diffuse, this approach captures short-run behavioral and cognitive responses rather than long-term adaptation or infrastructure effects.

5 Results

This section reports estimates of equation (1). My preferred estimator is Poisson Pseudo–Maximum Likelihood (PPML); I also report OLS as a linear benchmark. Unless otherwise noted, standard errors are clustered at the municipality level.

Table 2 presents the main effect of wildfire smoke on traffic accidents. Column (1) shows that, relative to smoke-free days within the same municipality–month, days with any smoke are associated with a $(e^{0.013} - 1) \times 100 \approx 1.3\%$ increase in expected daily accidents (PPML). Column (2) reports the OLS semi-elasticity of 2.5%. Because PPML with high-dimensional fixed effects automatically drops separated observations (Correia et al., 2020), Column (3) re-estimates OLS on the PPML sample for comparability; the implied effect is 3.4%. All approaches point to a positive effect of smoke presence on accidents. Based on the PPML estimate, the cumulative effect during the wildfire season (May–October) corresponds to approximately 2,477 additional accidents.

Table 2: Effect of Smoke Exposure on Traffic Accidents

	PPML	**OLS**	**OLS (PPML Sample)**
Smoke (Any)	0.013^{**}	0.025^{*}	0.034^{*}
	(0.005)	(0.014)	(0.019)
Observations	302,946	413,448	302,946
R^2/Pseudo R^2	0.8483	0.9310	0.9305
Month×Municipality FE	Yes	Yes	Yes
Year×Municipality FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Mean	2.98	2.19	2.98

Notes: Municipality-level SEs in parentheses. PPML drops separated observations by construction; Column (3) re-estimates OLS on the PPML sample. $^{*}p < 0.10$, ** $p < 0.05$, $^{***}p < 0.01$.

5.1 Heterogeneous Effects

I next examine heterogeneity along five dimensions motivated by the conceptual framework: smoke intensity, urban vs. rural, weekday vs. weekend, collision severity, and pre- vs. post-COVID. Throughout, I estimate PPML analogues of equation (1); OLS versions are reported in the appendix 1 and yield consistent qualitative conclusions.

By smoke intensity. Smoke exposure could plausibly affect accidents in two opposing ways: it may impair cognition and attention, increasing accident risk, but it can also trigger avoidance behavior, reducing travel when conditions are visibly poor. Whether the net effect is positive, negative, or nonlinear is therefore an empirical question. To test for this, I replace the single smoke indicator in equation (1) with separate indicators for light, medium, and heavy smoke intensity: LightSmoke_{idmy}, $\text{MediumSmoke}_{idmy}$, and HeavySmoke_{idmy}.

The results, presented in Table 3, reveal clear nonlinearity. Light and medium smoke are associated with increases of approximately 2.3% and 4.2% in daily accident counts, respectively, while heavy smoke reduces accidents by about 3.6%. This pattern is consistent with the idea that moderate smoke impairs cognitive performance, while more intense, perceptible smoke prompts drivers to avoid travel or adopt more cautious behavior.

Urban vs. rural. Table 4 estimates separate models for urban and rural municipalities. Light smoke raises accidents in urban areas but is insignificant in rural areas, consistent with higher baseline traffic density amplifying cognitive effects. Medium smoke is insignificant in urban areas but positive in rural areas, plausibly reflecting less scope for avoidance in rural labor markets. Heavy smoke reduces accidents in both settings, consistent with avoidance.

Weekday vs. weekend. If avoidance is easier on weekends, the cognition channel should be more visible on weekdays. Table 5 confirms that light smoke increases weekday accidents but not weekend accidents; heavy smoke reduces accidents on both.

Table 3: Effect of Smoke Exposure on Traffic Accidents (by Intensity)

	PPML	**OLS**	**OLS (PPML Sample)**
Light Smoke	0.023***	0.047**	0.065**
	(0.007)	(0.023)	(0.032)
Medium Smoke	0.042**	0.126**	0.142**
	(0.018)	(0.060)	(0.069)
Heavy Smoke	-0.036***	-0.076***	-0.106***
	(0.009)	(0.029)	(0.041)
Observations	302,946	413,448	302,946
R^2/Pseudo-R^2	0.840	0.930	0.931
Month×Municipality FE	Yes	Yes	Yes
Year×Municipality FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Mean	2.98	2.99	2.98

Notes: PPML estimates of equation (1) with smoke intensity dummies LightSmoke$_{idmy}$, MediumSmoke$_{idmy}$, HeavySmoke$_{idmy}$; municipality-clustered SEs. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4: Effect of Smoke Exposure on Traffic Accidents: Urban vs. Rural

	Urban	**Rural**
Light Smoke	0.026***	0.013
	(0.009)	(0.010)
Medium Smoke	0.020	0.074*
	(0.015)	(0.039)
Heavy Smoke	-0.025***	-0.079***
	(0.009)	(0.022)
Observations	202,297	100,649
Pseudo R^2	0.911	0.338
Month×Municipality FE	Yes	Yes
Year×Municipality FE	Yes	Yes
Controls	Yes	Yes
Mean	3.46	2.01

Notes: I present separate estimates for urban and rural municipalities based on equation 1. The urban sample includes cities, towns, villages, and summer villages. Standard errors are clustered at the municipality level. Significance level: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5: Effect of Smoke Exposure on Traffic Accidents: Weekday vs. Weekend

	Weekday	**Weekend**
Light Smoke	0.020***	-0.010
	(0.007)	(0.010)
Medium Smoke	0.005	0.062
	(0.023)	(0.038)
Heavy Smoke	-0.039***	-0.042**
	(0.009)	(0.015)
Observations	204,255	71,330
Pseudo R^2	0.857	0.817
Month×Municipality FE	Yes	Yes
Year×Municipality FE	Yes	Yes
Controls	Yes	Yes
Mean	3.35	3.05

Notes: Standard errors are clustered at the municipality level. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

By collision severity. Table 6 presents the estimated effects of wildfire smoke exposure by accident severity. The point estimates for light and medium smoke are positive across all categories — fatal, injury, and property-damage-only accidents — although statistical significance varies. Light smoke significantly increases property-damage-only accidents, while medium smoke significantly increases both fatal and property-damage accidents. The larger point estimates for medium relative to light smoke, particularly for fatalities and property damage, are consistent with increasing cognitive impairment as exposure intensifies. In contrast, heavy smoke significantly reduces accidents across all severity categories, including fatalities, injuries, and property damage, consistent with avoidance behavior when smoke is highly visible and salient.

Pre- vs. post-COVID. Table 7 estimates separate models for periods before and after the COVID-19 shock to commuting patterns. The ability and acceptance to work from home increased substantially during the pandemic. Light and medium smoke increase accidents in the pre-COVID period but have no significant effects post-COVID, while heavy smoke

Table 6: Effect of Smoke Exposure on Traffic Accidents by Collision Severity

	Fatal	**Injury**	**Property Damage**
Light smoke	0.0596	0.0472***	0.0193***
	(0.1004)	(0.0174)	(0.0070)
Medium smoke	0.5628**	0.0321	0.0403**
	(0.2655)	(0.0569)	(0.0176)
Heavy smoke	-0.0079	-0.0443**	-0.0347***
	(0.1523)	(0.0213)	(0.0095)
Observations	57,009	200,447	299,447
Pseudo R^2	0.1003	0.5754	0.8441
Month×Municipality FE	Yes	Yes	Yes
Year×Municipality FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Mean	0.048	0.54	2.65

Notes: The number of observations differs across columns because accident incidents vary in severity, especially since only a few accidents result in fatalities. Additionally, PPML also automatically drops separated observations within each category. Standard errors are clustered at the municipality level. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

reduces accidents — especially after COVID — consistent with greater scope for avoidance when remote work is more prevalent.

6 Mechanisms

The heterogeneity analysis provides suggestive evidence that light and medium smoke increase accidents through impaired cognitive function, whereas heavy smoke reduces accidents through avoidance behavior. This section explores those channels more directly.

First, I examine how wildfire smoke affects traffic volumes. Traffic flow data, available only for Calgary during 2022–2024, record the daily number of vehicles captured by traffic cameras across major intersections. I regress these traffic counts on indicators for wildfire smoke exposure, controlling for calendar month and year fixed effects. As before, identification relies on within-city, day-to-day variation in smoke intensity across the wildfire season. The results, reported in Table 8, show no statistically significant change in vehicle counts on days

Table 7: Effect of Smoke Exposure on Traffic Accidents: Pre- vs. Post-COVID

	Pre-COVID	**Post-COVID**
Light Smoke	0.029***	-0.018
	(0.007)	(0.014)
Medium Smoke	0.064***	0.011
	(0.016)	(0.031)
Heavy Smoke	-0.024	-0.081***
	(0.014)	(0.009)
Observations	166,126	120,705
Pseudo R^2	0.856	0.827
Month×Municipality FE	Yes	Yes
Year×Municipality FE	Yes	Yes
Controls	Yes	Yes
Mean	3.48	2.70

*Notes:*Standard errors are clustered at the municipality level.
Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

with any smoke. When disaggregated by intensity, heavy smoke significantly reduces traffic volumes, consistent with avoidance behavior and with the corresponding decline in accidents under severe smoke conditions. In contrast, light smoke has no detectable effect, and medium smoke — if anything — increases traffic volumes. This pattern suggests that individuals do not perceive light or moderate smoke as hazardous and therefore do not alter their travel behavior, a finding that is particularly salient given the sample is from post–COVID-19, when remote work and flexible commuting could have facilitated avoidance if the risk were perceived.

Visibility might be one potential channel through which wildfire smoke exposure may affect accidents by directly reducing visibility. To investigate this further, I estimate equation 3 with visibility (in km) as the outcome variable rather than accidents. Table 9 shows the results from this estimation. Smoke significantly reduces visibility, with heavy smoke lowering it by nearly 36%. Although smoke reduces visibility, the magnitude of this reduction is likely too small to affect driving conditions. The average visibility is 23.08 km, even under heavy smoke, visibility declines by an average of 8.8 km, leaving an average visibility of about 15 km, which remains sufficient for safe driving. Because smoke and visibility are not perfectly correlated, I can restrict the sample to days with at least 25 km visibility and re-estimate the main model. Table 10 shows results that are consistent with the baseline estimates. These findings indicate that while wildfire smoke reduces visibility, the reduction is likely insufficient to explain the increase in accidents. Therefore, visibility is not a meaningful channel through which smoke influences traffic accidents.

Table 8: Effect of Smoke Exposure on Traffic Flow

	Any Smoke	**Smoke Intensity**
Any Smoke	-11.085	
	(6.958)	
Light Smoke		-8.242
		(7.018)
Medium Smoke		82.659***
		(24.324)
Heavy Smoke		-55.567***
		(12.198)
Observations	83,105	83,105
R-squared (within)	0.0218	0.0222
Month FE	Yes	Yes
Year FE	Yes	Yes
Controls	Yes	Yes
Mean	1,636.3	1,636.3

Notes: The dependent variable is the number of vehicles recorded by traffic cameras in Calgary. Observations are at the camera–day level. Standard errors are robust to heteroskedasticity. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

To further explore the potential effects of visibility on accidents, I consider time of day. I divide each day into six four-hour intervals, from 7:00 a.m.–10:59 a.m. through 3:00 a.m.–6:59 a.m., and estimate the main model separately for each period. Table 11 presents the results. If reduced visibility were the primary channel, accident rates should increase at night when baseline visibility is lowest. Instead, the opposite pattern emerges: accidents rise under light smoke during daytime and rush-hour periods—when visibility is naturally high—and disappear at night. This finding rules out visibility as the dominant mechanism. Rather, the daytime increase in accidents aligns with cognitive impairment from smoke exposure, while the decline in accidents under heavy smoke reflects avoidance behavior, as individuals delay or forego travel when conditions are visibly poor. Together, the evidence indicates that wildfire smoke affects accidents through two distinct mechanisms: impaired cognition, which increases accident risk when smoke is not salient, and behavioral avoidance, which reduces accidents when the hazard is perceptible.

Table 9: Effect of Smoke Exposure on Visibility (km)

Light Smoke	-1.584***
	(0.117)
Medium Smoke	-4.072***
	(0.333)
Heavy Smoke	-8.800***
	(0.371)
Observations	359,209
R^2	0.6192
Month×Municipality FE	Yes
Year×Municipality FE	Yes
Controls	Yes
Mean	23.08

Notes: I regress visibility on smoke intensity. Standard errors clustered at the municipality level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Effect of Smoke Exposure on Traffic Accidents on High-Visibility (>25 km) Days

	PPML
Light Smoke	0.042***
	(0.0128)
Medium Smoke	0.061*
	(0.0375)
Heavy Smoke	-0.047**
	(0.0222)
Observations	116,432
Pseudo R^2	0.860
Month×Municipality FE	Yes
Year×Municipality FE	Yes
Controls	Yes
Mean	3.13

Notes: I regress visibility on smoke intensity using only high-visibility (>25 km) days. Standard errors clustered at the municipality level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Effect of Smoke Exposure on Traffic Accidents by Time of Day

	7-11	**11-15**	**15 -19**	**19-23**	**23 -3**	**3 - 7**
Light Smoke	0.0198*	0.0301**	0.0293***	0.0312**	-0.0099	-0.0393
	(0.0118)	(0.0125)	(0.0069)	(0.0128)	(0.0211)	(0.0266)
Medium Smoke	0.0705	0.0326	0.0531	0.0741	-0.0816	0.1058
	(0.0438)	(0.0261)	(0.0325)	(0.0496)	(0.0883)	(0.0688)
Heavy Smoke	-0.0781***	-0.0267*	-0.0143	-0.0443	-0.0183	-0.0833**
	(0.0200)	(0.0144)	(0.0137)	(0.0529)	(0.0309)	(0.0280)
Observations	223,525	245,209	239,215	214,598	173,589	172,067
Pseudo R^2	0.6935	0.7559	0.7871	0.5883	0.4851	0.4208
Month×Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year×Municipality	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean	0.66	0.92	1.13	0.60	0.26	0.25

Notes: This table presents separate estimates of the main model for different times of the day. The number of observations differs across columns because accident incidents vary by time of day, and PPML also automatically drops separated observations within each category. Standard errors are clustered in Municipality level. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

7 Conclusion

Wildfires are becoming a dominant source of global air pollution, and their smoke now reaches populations far from the fireline. This paper provides evidence that wildfire smoke also affects an essential yet understudied domain of behavior—road safety. Using municipality–day data from Alberta combined with satellite-based smoke maps, I show that accident rates rise on light and medium smoke days but fall on heavy smoke days, revealing a nonlinear relationship driven by the interaction of cognition and avoidance. Complementary evidence from traffic counts and visibility measures suggests that smoke impairs performance even when it is not perceptible enough to alter driving behavior, while severe smoke triggers avoidance and fewer trips. These results highlight an overlooked welfare cost of wildfire smoke: degraded cognitive function and decision quality that endanger public safety. As wildfires intensify with climate change, policies that communicate the risks of even mild smoke exposure—and encourage reduced travel during smoky periods—could yield substantial health and safety benefits.

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Appendix 1

Table 12: Effect of Smoke Exposure on Traffic Accidents: Urban vs. Rural

	Urban	**Urban (PPML Sample)**	**Rural**	**Rural Sample**
Light Smoke	0.053*	0.083*	0.028	0.028
	(0.030)	(0.046)	(0.021)	(0.021)
Medium Smoke	0.059	0.086	0.157*	0.160*
	(0.094)	(0.136)	(0.080)	(0.081)
Heavy Smoke	-0.057*	-0.089*	-0.146***	-0.147***
	(0.034)	(0.053)	(0.045)	(0.045)
Observations	311,696	202,297	101,752	100,649
R^2	0.9362	0.9357	0.4698	0.4680
Month×Municipality FE	Yes	Yes	Yes	Yes
Year×Municipality FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Mean	2.24	3.46	2.03	2.05

Notes: This table presents the separate estimates for urban and rural municipalities using the OLS approach and specification in equation (1). Standard errors are clustered at the municipality level. Urban samples include cities, towns, villages, and summer villages. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 13: Effect of Smoke Exposure on Traffic Accidents: Weekday vs. Weekend Samples

	Weekday	**Weekday (PPML Sample)**	**Weekend**	**Weekend (PPML Sample)**
Light Smoke	0.043**	0.063**	-0.019	-0.032
	(0.020)	(0.029)	(0.022)	(0.036)
Medium Smoke	-0.015	-0.022	0.149	0.159
	(0.102)	(0.124)	(0.099)	(0.114)
Heavy Smoke	-0.087***	-0.130***	-0.074*	-0.128*
	(0.031)	(0.046)	(0.042)	(0.073)
Observations	294,999	204,255	118,449	71,330
R^2	0.9460	0.9456	0.9429	0.9422
Month×Municipality FE	Yes	Yes	Yes	Yes
Year×Municipality FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Mean	2.34	3.38	1.88	3.05

Notes: I present separate estimates for weekdays and weekends using OLS approach. Standard errors are clustered in municipality level. Significance level: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 14: Effect of Smoke Exposure on Traffic Accidents: Pre- vs. Post-COVID

	Pre-COVID	**Pre-COVID (PPML Sample)**	**Post-COVID**	**Post-COVID (PPML Sample)**
Light Smoke	0.069*	0.099*	-0.027	-0.038
	(0.038)	(0.055)	(0.032)	(0.047)
Medium Smoke	0.206**	0.259**	0.044	0.025
	(0.086)	(0.108)	(0.100)	(0.107)
Heavy Smoke	-0.045*	-0.070*	-0.153**	-0.227**
	(0.025)	(0.038)	(0.064)	(0.095)
Observations	236,256	166,126	177,192	120,705
R^2	0.9323	0.9319	0.9315	0.9310
Month×Municipality FE	Yes	Yes	Yes	Yes
Year×Municipality FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Mean	2.42	3.44	1.88	2.77

Notes: I present separate estimates for pre- and post-COVID periods using OLS approach. Standard errors are clustered at the municipality level. Significance level: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

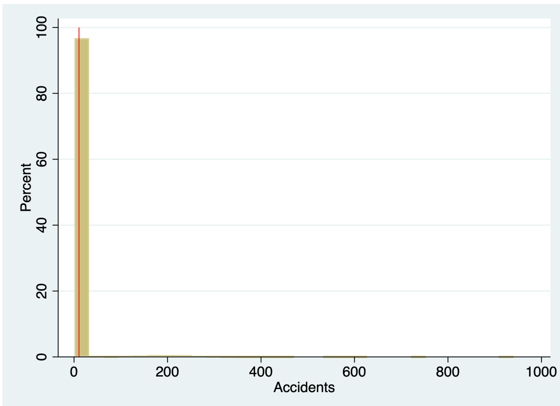
Table 15: Effect of Smoke Exposure on Traffic Accidents by Collision Severity

	Fatal	**Fatal (PPML)**	**Injury**	**Injury (PPML)**	**Property Damage**	**Property Damage (PPML)**
Light Smoke	0.0004	0.0032	0.012*	0.025*	0.034*	0.048*
	(0.0007)	(0.0050)	(0.006)	(0.013)	(0.018)	(0.025)
Medium Smoke	0.0107	0.038*	0.013	0.015	0.102*	0.116*
	(0.0067)	(0.0221)	(0.023)	(0.031)	(0.058)	(0.067)
Heavy Smoke	-0.0002	-0.0011	-0.010**	-0.024**	-0.065**	-0.093**
	(0.0010)	(0.0082)	(0.005)	(0.011)	(0.027)	(0.038)
Observations	413,448	57,009	413,448	200,447	413,448	299,447
R^2	0.0231	0.0158	0.6882	0.6816	0.9280	0.9276
Within R^2	0.0001	0.0003	0.0003	0.0007	0.0009	0.0012
Clusters (Municipalities)	321	117	321	228	321	309
Month×Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year×Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean	0.0066	0.0479	0.274	0.565	1.91	2.64

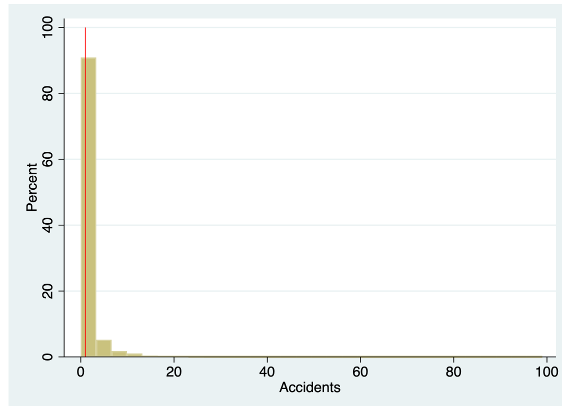
Notes: I present separate estimates by collision severity using an OLS approach. Standard errors are clustered at the municipality level. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix 2

Figure 1: Distribution of Accidents

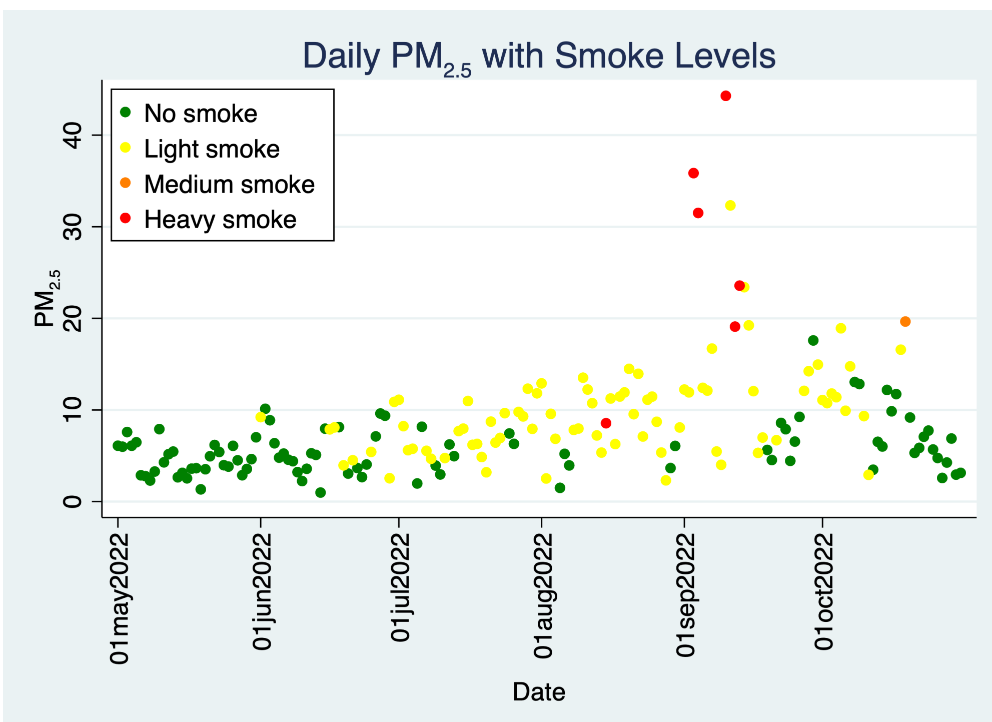


(a) Distribution of daily municipality-level accidents for the full sample



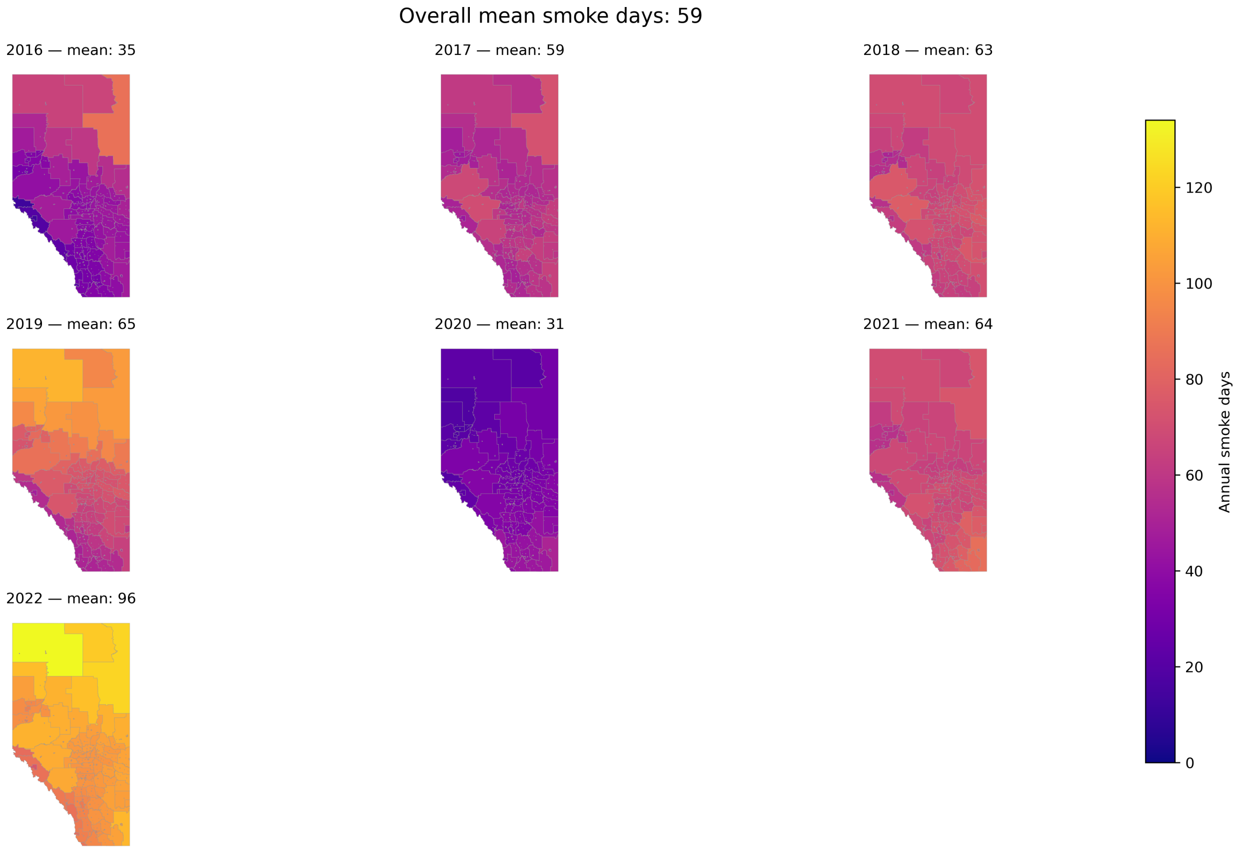
(b) Distribution of daily municipality-level accidents, when number of daily accidents < 100

Figure 2: Association of Smoke and PM2.5



Note: This figure shows the association between PM2.5 and smoke intensity in the City of Edmonton during the 2022 smoke season (May–October)

Figure 3: Yearly Number of Smoke Days in Municipalities in Alberta



Note: This figure shows the annual count of smoke days for any intensity across the municipalities of Alberta over the period 2016 - 2022.