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 traffic accidents increase on days with light or moderate smoke exposure but decrease on days with heavy smoke. Traffic volume data show no change in vehicle counts during light smoke exposure but substantial reductions during heavy smoke events, consistent with drivers reducing travel when smoke conditions become more severe. These findings suggest that behavioral responses to smoke exposure may help explain the nonlinear relationship between wildfire smoke and traffic accidents. During lighter smoke events, drivers may continue traveling despite conditions that increase accident risk, whereas more severe smoke appears to induce reductions in driving. The results highlight a potentially overlooked cost of wildfire smoke and suggest that drivers' behavioral responses may depend on the severity of smoke exposure.

Key Words: Wildfire, Smoke, Accidents, Cognitive, Avoidance
JEL Codes: Q53, Q52, R41, I18

Abstract

*Acknowledgements: I Would like to thank my supervisor, Dr. Erica Myers, for her guidance and wonderful comments. I am thankful to my committee members, Dr. Benjamin Crost and Lucija Muehlenbachs, for their invaluable comments. This paper also benefited from comments and suggestions by the Internal Departmental Seminar at the University of Calgary, the CEA annual conference 2025, and the CREEA yearly conference 2025. All errors are my own.

1 Introduction

Wildfires have intensified dramatically over the past two decades, with the global area of tree cover burned more than doubling over this period (Potapov et al., 2025). Recent years have been particularly severe, with 2021, 2023, and 2024 ranking among the worst years globally for forest loss due to fires.[1] Wildfires release a complex mixture of pollutants, including greenhouse gases, photochemically reactive compounds, and fine and coarse particulate matter (PM) (Urbanski et al., 2008). The scale of the 2023 Canadian wildfires illustrates the severity of these events. Canadian wildfires emitted approximately 647 TgC of carbon that year, exceeding the annual fossil fuel emissions of every country except India, China, and the United States (Byrne et al., 2024). On May 16, 2023, $PM_{2.5}$ concentrations in southeast Calgary reached 558 $\mu g/m^3$, illustrating the extreme levels of air pollution that wildfire smoke can generate in urban areas. Toxicological evidence further suggests 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). The effect of wildfire smoke on traffic accidents is theoretically ambiguous: smoke exposure may increase accident risk by impairing visibility or driving performance, but it may also reduce accidents if drivers respond by limiting travel. The net

[1] See https://www.wri.org/insights/global-trends-forest-fires, and https://www.preventionweb.net/news/latest-data-confirms-forest-fires-are-getting-worse

effect may therefore depend on smoke intensity and the extent to which drivers adjust their behavior. Evidence on wildfire smoke and traffic accidents is mixed (Aguilera et al., 2026; Hetalo, 2024a,b). 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. I also use supplementary traffic volume data from Calgary to investigate whether changes in driving behavior help explain the observed patterns.

The empirical strategy exploits day-to-day variation in smoke exposure within municipality-by-month-by-year cells. Because wildfire smoke can travel long distances (Miller et al., 2017) and fluctuate sharply over space and time, its arrival generates short-run variation in local pollution exposure that is plausibly unrelated to changes in driving conditions after controlling for weather and municipality-by-month-by-year fixed effects. 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 conditions and time-varying municipality-specific factors using municipality-by-month-by-year fixed effects. This design isolates the short-run effect of smoke exposure on accident rates while minimizing confounding from correlated local shocks.

Using this approach, I find a striking nonlinear relationship between wildfire smoke exposure and traffic accidents. 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 are consistent with drivers reducing travel when smoke is severe, while maintaining their usual travel during less intense smoke exposure. The increase in accidents during lighter smoke exposure, when traffic volumes remain largely unchanged, is consistent with smoke increasing accident risk without inducing offsetting reductions in driving. By contrast, the decline in accidents during heavy smoke events may

reflect behavioral avoidance as drivers reduce their travel. Together, these findings suggest that wildfire smoke can pose risks to road safety even when it does not lead to observable changes in driving behavior.

This paper contributes to two strands of the literature. First, and most directly, it contributes to the literature on air pollution and road safety. Previous studies have documented mixed effects of pollution on traffic accidents, with some finding increases in crash counts (Sager, 2019; Wang et al., 2023; Shi et al., 2022; Baryshnikova and Wesselbaum, 2023; Burton and Roach, 2026) and others finding reductions in severe accidents, consistent with greater caution or avoidance (Shr et al., 2023; Deng et al., 2024). More recent studies have examined wildfire smoke specifically. Aguilera et al. (2026) find mostly inverse but imprecise associations between wildfire $PM_{2.5}$ and motor vehicle crashes in California, while Hetalo (2024a,b) documents increases in fatal crashes in the Western United States and nonlinear effects of smoke exposure on serious accidents in British Columbia. Building on this work, I use daily administrative data covering all reported accidents in Alberta, including property-damage-only crashes. I also use traffic volume data from Calgary to investigate behavioral avoidance, finding that driving volumes decline under heavy smoke but remain unchanged under light smoke. The visibility analysis further suggests that reduced visibility alone cannot explain the increase in accidents. Together, these analyses shed light on the behavioral responses underlying the nonlinear relationship between wildfire smoke and road safety.

Second, the study contributes to the growing literature on the economic consequences of wildfire smoke. Previous research has examined its effects on health (Miller et al., 2024; Grant and Runkle, 2022), labor market outcomes (Borgschulte et al., 2022), productivity (Cvijanovic et al., 2024), and school performance and cognitive outcomes (Wen and Burke, 2022). This paper contributes to literature by documenting an additional consequence of wildfire smoke: changes in traffic accidents and associated public safety costs. The findings also provide evidence of behavioral adaptation that varies with smoke intensity: driving

volumes decline during heavy smoke events but remain largely unchanged during lighter smoke exposure, even as accident counts increase.

Finally, the results have implications for public safety policy and risk communication. The finding that accidents increase during light smoke exposure without a corresponding decline in traffic volume suggests that drivers may not fully account for the risks associated with less severe smoke events. This highlights the potential value of communicating road safety risks even when smoke exposure is relatively low.

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, driving ability, and avoidance behavior. Section 4 outlines the empirical identification strategy. Section 5 reports the main results and heterogeneity analyses. Section 6 explores potential mechanisms, Section 7 presents robustness checks,and Section 8 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 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. The dataset contains accident data covering all of Alberta, including highways, major roads, and smaller roads, providing a representative picture of travel and accidents across the province. 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 spatially overlaid with Alberta's municipal boundaries to calculate the percentage of each municipality covered by wildfire smoke. A municipality is classified as exposed on a given day if a smoke plume covers more than 50% of its area. I use this classification to construct municipality-day indicators for smoke exposure and, based on the reported smoke-density classifications, indicators for light, medium, and heavy smoke [2]. To control for weather, I use hourly temperature, precipitation, and visibility data from Environment and Climate Change Canada (ECCC). I aggregate hourly observations to the daily level and construct municipality-level measures as inverse distance-weighted averages of all stations within 100 kilometers of each municipality centroid, following Borgschulte et al. (2022). I also use hourly $PM_{2.5}$ concentrations from ECCC's National Air Pollution Surveillance (NAPS) Program, aggregated to the municipality-day level in the same way as weather variables.

Finally, to examine whether wildfire smoke changes travel behavior, I use traffic volume data from Statistics Canada. Statistics Canada uses 191 unique cameras in the city of Calgary as of Oct 2024, counts vehicles passing through each camera in 5-minute intervals, and aggregates the data to the daily level. These data are available only for 2022–2024, whereas the main accident analysis covers 2016–2022. I drop the 43 days from my sample when no camera reports any data. The resulting panel is unbalanced. These daily traffic volumes proxy the number of vehicles on the road and let me test whether heavy smoke discourages travel.

The accident, smoke, and ambient air pollution datasets are merged at the municipality-day level using consistent spatial identifiers[3]. The resulting panel contains information on road accidents, smoke plume coverage, ambient air pollution, and weather for 2016–2022. The Calgary traffic data are analyzed separately to assess avoidance behavior. Table 1 reports summary statistics for the primary dataset.

[2]When multiple smoke densities overlap a municipality-day, I assign the density of the polygon covering the largest area.

[3]Wildfire smoke exposure occurs almost exclusively during the May–October wildfire season. Restricting the sample to this period focuses on the relevant support of the treatment and avoids introducing substantial additional variation in accidents driven by winter driving conditions (e.g., snow and ice), which would reduce the precision of the estimates.

Table 1: Summary Statistics

Variable	Obs	Mean	Std. Dev.
Accidents	412,160	0.95	7.461
Smoke (any)	412,160	0.31	0.461
Smoke (light)	412,160	0.25	0.430
Smoke (medium)	412,160	0.01	0.083
Smoke (heavy)	412,160	0.05	0.228
Smoke coverage (%)	412,160	30.70	45.791
$PM_{2.5}$ ($\mu g/m^3$)	386,214	7.58	11.679
Temperature (°C)	412,012	12.49	6.242
Precipitation (mm)	412,160	1.17	5.001
Visibility (km)	357,948	23.09	7.918

Notes: Observations are at the municipality-day level.

3 Conceptual Framework

Wildfire smoke can affect accident counts through two competing mechanisms: a direct effect on driving ability and an indirect effect through changes in driving behavior. Let W denote smoke exposure, C driving ability, and N the number of vehicles on the road. The probability that a representative driver completes a trip without an accident 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:

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

If smoke exposure reduces driving ability ($\frac{\partial C}{\partial W} < 0$) and discourages travel ($\frac{\partial N}{\partial W} < 0$), and greater traffic volume increases accident risk ($\frac{\partial \Phi}{\partial N} < 0$), the direct effect increases accidents while the indirect effect 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 the causal effect of smoke exposure on accident counts and uses supplementary traffic volume data to investigate the role of behavioral responses.

4 Empirical Strategy

Consistent with the conceptual framework, I estimate the effect of wildfire smoke exposure on daily accident counts, exploiting day-to-day variation in smoke exposure within municipality-by-month-by-year cells while controlling for weather conditions.

Formally, I estimate the following equation:

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

where Accidents_{idmy} is the number of 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.[4] X_{idmy} is a vector of weather controls including daily temperature, and precipitation. λ_{imy} denotes municipality-by-month-by-year fixed effects that absorb factors that are constant within each municipality-month, such as population, infrastructure, and persistent differences in 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. Formally, $(\exp(\beta_1) - 1) \times 100$ gives this percentage change.

The identification strategy exploits daily variation in smoke exposure that is plausibly 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. Unlike locally generated pollution, which may be correlated with traffic conditions or economic activity, wildfire smoke dispersion is driven primarily by meteorological factors rather than local driving behavior. As a result,

[4] A municipality is considered covered by smoke if more than 50% of its land area lies within a smoke plume polygon, based on NOAA HMS data.

its short-run arrival in a given area is plausibly exogenous to traffic conditions.[5]

Nonetheless, remaining concerns could arise if smoke exposure coincides with unobserved factors that also affect accident risk (e.g., changes in precipitation or temperature). I therefore include daily mean temperature and precipitation as weather controls and absorb municipality-by-month-year fixed effect to isolate day-to-day variation in smoke exposure within these cells. Standard errors are clustered at the municipality level, allowing for arbitrary spatial correlation in unobservable within the municipality.

The dependent variable, the number of daily accidents, is non-negative and highly skewed. While OLS in levels provides a useful linear benchmark, it imposes a linear conditional mean and yields estimates in levels that may be difficult to compare across settings with different baseline accident rates. Instead, I estimate equation (1) using the Poisson Pseudo-Maximum Likelihood (PPML) estimator, which models the conditional mean as an exponential function of the covariates and yields coefficients that can be interpreted as semi-elasticities. PPML is also robust to general forms of heteroskedasticity (Wooldridge, 2009) and accommodates 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 driving ability and avoidance behavior, I estimate equation (1) with separate indicators for light, medium and heavy smoke:

$$\begin{aligned} \text{Accidents}_{idmy} = \exp\big(&\alpha + \beta_L \,\text{LightSmoke}_{idmy} + \beta_M \,\text{MediumSmoke}_{idmy} \\ &+ \beta_H \,\text{HeavySmoke}_{idmy} + \gamma' X_{idmy} + \lambda_{imy}\big)\epsilon_{idmy}. \end{aligned} \tag{2}$$

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

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

days within the same municipality, month and year. 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 driving ability 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 1.5%[6], which is insignificant. 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 positive but not significant. All approaches point to a positive effect of smoke presence on accidents. Based on the PPML estimate.

5.1 Heterogeneous Effects

I next examine heterogeneity along four dimensions motivated by the conceptual framework: smoke intensity, urban vs. rural, collision severity, and pre- vs. post-COVID. Throughout, I estimate PPML analogues of equation (1). Corresponding OLS specifications, along with alternative fixed effects structures incorporating municipality-by-month and municipality-by-year fixed effects, are reported in Appendix 1 and yield qualitatively similar conclusions.

[6]For comparability with the semi-elasticities obtained from the PPML estimator, I present OLS coefficients as percentages relative to the sample mean of the outcome variable.

Table 2: Effect of Smoke Exposure on Traffic Accidents

	PPML	**OLS**	**OLS (PPML Sample)**
Smoke (Any)	0.013^{***}	0.014	0.023
	(0.005)	(0.009)	(0.015)
Observations	248,073	412,012	248,073
R^2/Pseudo R^2	0.814	0.934	0.933
Month×Year×Municipality FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Mean	1.58	0.95	1.58

Notes: Standard errors are clustered at the municipality level and reported in parentheses. The number of clusters in the PPML estimation is 310, and in OLS it is 320. All specifications control for temperature bins and precipitation and include municipality-by-month-by-year fixed effects. PPML drops singleton and separated observations; therefore, the number of observations differs between the PPML and OLS specifications. Column (3) re-estimates OLS using the PPML estimation sample. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

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 1.8% and 5.4% in daily accident counts, respectively, while heavy smoke reduces accidents by about 3.5%. 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 and medium smoke raises accidents in urban areas but is positive and insignificant in rural areas. One possible explanation is that higher baseline traffic density in urban areas amplifies the impact of smoke exposure. Heavy smoke reduces accidents in both settings,

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

	PPML	**OLS**	**OLS (PPML Sample)**
Light Smoke	0.018***	0.018*	0.031*
	(0.006)	(0.011)	(0.018)
Medium Smoke	0.053***	0.081*	0.099*
	(0.014)	(0.042)	(0.053)
Heavy Smoke	-0.034***	-0.028***	-0.051***
	(0.011)	(0.009)	(0.016)
Observations	248,073	412,012	248,073
R^2/Pseudo-R^2	0.814	0.934	0.933
Month×Year×Municipality FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Mean	1.58	0.95	1.58

Notes: This table presents estimation results for equation (2). Standard errors are clustered at the municipality level and reported in parentheses. The number of clusters in the PPML estimation is 310, and in OLS it is 320. All specifications control for temperature bins and precipitation and include municipality-by-month-by-year fixed effects. PPML drops singleton and separated observations; Column (3) re-estimates OLS on the PPML sample. The omitted category is no smoke. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

consistent with avoidance behavior.

By collision severity. Table 5 presents the estimated effects of wildfire smoke exposure by accident severity. There is no statistically significant effect on fatal accidents, likely reflecting their low baseline incidence and limited statistical power, further compounded by the loss of observations due to separation in the PPML estimation. Light and medium smoke do not have statistically significant effects on injury accidents but are associated with increases in property-damage-only accidents. In contrast, heavy smoke significantly reduces both injury and property-damage-only accidents. These results indicate heterogeneous effects across severity categories and are broadly consistent with the idea that smoke exposure increases minor driving errors, while severe smoke induces avoidance behavior. Property damage accidents increased by 328 on light and medium smoke days.

Pre- vs. Post-COVID. Table 6 estimates separate models for periods before and after the COVID-19 shock to commuting patterns. The ability and acceptance to work from

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

	Urban	**Rural**
Light Smoke	0.023***	0.003
	(0.006)	(0.012)
Medium Smoke	0.057***	0.033
	(0.009)	(0.034)
Heavy Smoke	-0.022**	-0.086***
	(0.010)	(0.023)
Observations	149,678	98,395
Pseudo R^2	0.89	0.28
Month×Year×Municipality FE	Yes	Yes
Controls	Yes	Yes
Mean	2.05	0.88

Notes: I present separate estimates for urban and rural municipalities. 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 by Collision Severity

	Fatal	**Injury**	**Property Damage**
	(1)	(2)	(3)
Light Smoke	-0.004	0.031	0.016***
	(0.100)	(0.022)	(0.005)
Medium Smoke	0.313	-0.025	0.061***
	(0.216)	(0.046)	(0.015)
Heavy Smoke	-0.156	-0.062**	-0.031**
	(0.137)	(0.026)	(0.012)
Observations	23,778	147,675	244,531
Pseudo R^2	0.03	0.50	0.81
Month×Year×Municipality FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Mean	0.042	0.28	1.43

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 automatically drops separated observations within each category. Standard errors are clustered at the municipality level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

home increased substantially during the pandemic. Light and medium smoke increases accidents in the pre-COVID period, and heavy smoke have no statistically significant effect. In contrast, light and medium smoke have no statistically significant effect on accidents after COVID. Heavy smoke is associated with a much larger reduction in accidents after COVID, consistent with greater opportunities for avoidance as remote work became more prevalent. The post-COVID period covers 2020–2022, when COVID-related restrictions were still in place. The positive but statistically insignificant effects of light and medium smoke during the post-COVID period are consistent with reduced traffic volumes, which may attenuate the overall impact of smoke exposure on accidents.

Table 6: Effect of Smoke Exposure on Traffic Accidents: Pre- vs. Post-COVID

	Pre-COVID	**Post-COVID**
Light Smoke	0.024^{***}	0.005
	(0.008)	(0.008)
Medium Smoke	0.062^{***}	0.035
	(0.015)	(0.025)
Heavy Smoke	-0.016	-0.059^{***}
	(0.015)	(0.010)
Observations	143,288	104,785
Pseudo R^2	0.83	0.79
Month×Year×Municipality FE	Yes	Yes
Controls	Yes	Yes
Mean	1.75	1.36

Notes: Standard errors are clustered at the municipality level. The pre-COVID period covers 2016–2019, while the post-COVID period covers 2020–2022. All specifications include temperature bins, precipitation. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

6 Mechanisms

Wildfire smoke is a leading cause of poor air quality in Canada[7]. Air pollution can affect accidents through three main channels: driving behavior(avoidance), reduced visibility (Intini et al., 2022); and cognitive impairment (Burton and Roach, 2026). The heterogeneity analysis provides suggestive evidence on which of these channels matter: light and medium smoke appear to increase accidents by impairing driving ability, suggesting reduced cognitive performance, whereas heavy smoke reduces accidents through avoidance. This section examines these 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. Identification relies on within-municipality, day-to-day variation in smoke intensity within the wildfire season. The results, reported in Table 7, show no statistically significant change in vehicle counts on days 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 is consistent with the idea that lower levels of smoke are not sufficiently salient to induce behavioral adjustment, whereas severe smoke leads to reductions in travel. This finding is particularly notable given the sample is from post–COVID-19, when remote work and flexible commuting could have facilitated avoidance if the risk were perceived.

Second, I estimate equation 1 with visibility (in km) as the outcome variable rather than accidents. Table 8 shows the results from this estimation. Smoke significantly reduces visibility, with heavy smoke lowering it by nearly 31%. Despite this reduction, average

[7]See https://www.canada.ca/en/health-canada/services/publications/healthy-living/wildfire-smoke-health.html.

visibility remains relatively high: from a baseline of 23.09 km, heavy smoke reduces visibility by about 7.08 km, leaving an average of approximately 16 km. Because smoke exposure and visibility are not perfectly correlated, it is possible to observe days with smoke but relatively high visibility. To more directly assess whether visibility drives the main results, I restrict the sample to days with high visibility (greater than 25 km) and re-estimate the baseline specification. Table 9 shows results that are broadly consistent with the baseline estimates. Medium-smoke effects are no longer statistically significant, likely reflecting the reduced sample size. These findings suggest that while wildfire smoke reduces visibility, changes in visibility alone are unlikely to explain the observed increase in accidents.

Table 7: Effect of Smoke Exposure on Traffic Flow

	Any Smoke		**Smoke Intensity**	
	(1)	(2)	(3)	(4)
Any Smoke	-11.085	-8.037		
	(6.958)	(5.039)		
Light Smoke			-8.242	-6.364
			(7.018)	(4.956)
Medium Smoke			82.659***	91.468***
			(24.324)	(12.371)
Heavy Smoke			-55.567***	-52.715***
			(12.198)	(8.275)
Observations	83,105	83,105	83,105	83,105
R-squared (within)	0.0218	0.0165	0.0222	0.0176
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Camera FE		Yes		Yes
Controls	Yes	Yes	Yes	Yes
Mean	1,636.3	1,636.3	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. All specifications control for temperature bins and precipitation. Columns (1) and (3) report heteroskedasticity-robust standard errors; columns (2) and (4) reports standard errors at the camera level. Standard errors in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

To examine whether drivers adjust their travel in response to smoke, I exploit variation in accident timing. I divide each day into a daytime window (7:00 a.m.- 7:00 p.m.) and a nighttime window (7:00 p.m.- 7:00 a.m.) and estimate the main specification separately for each. Table 10 reports the results. The nonlinear pattern in the main estimates is driven by daytime accidents: daytime accidents increase on light- and medium-smoke days and decline on heavy-smoke days. It is consistent with daytime travel being dominated by commuting and other routine trips. When smoke is light or moderate, it does not appear severe enough to deter these trips, so smoke exposure while driving raises accidents. The reduction in daytime accidents is consistent with the reduction in vehicles on the road. Nighttime accidents, by contrast, show no statistically significant response to light and medium smoke; however, accidents decline during heavy-smoke hours. This is consistent with the already lower number of trips at night; therefore, the negative effects of light and medium smoke are not present.

Table 8: Effect of Smoke Exposure on Visibility (km)

Light Smoke	-1.080***
	(0.091)
Medium Smoke	-2.015***
	(0.246)
Heavy Smoke	-7.088***
	(0.291)
Observations	357,948
R^2	0.6774
Month×Year×Municipality FE	Yes
Controls	Yes
Mean	23.09

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

Table 9: Effect of Smoke Exposure on Traffic Accidents on High-Visibility (>25 km) Days

	Accidents
Light Smoke	0.028**
	(0.013)
Medium Smoke	0.047
	(0.037)
Heavy Smoke	-0.094***
	(0.025)
Observations	64,054
Pseudo R^2	0.857
Month×Year×Municipality FE	Yes
Controls	Yes
Mean	2.34

Notes: I re-estimate equation (1) using the sub-sample of high-visibility (>25 km) days. Standard errors are clustered at the municipality level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Effect of Smoke Exposure on Traffic Accidents by Day and Night

	Day (7–19)	**Night (19–7)**
Light Smoke	0.026***	-0.009
	(0.004)	(0.010)
Medium Smoke	0.074***	0.013
	(0.016)	(0.034)
Heavy Smoke	-0.023***	-0.068**
	(0.008)	(0.028)
Observations	230,098	188,240
Pseudo R^2	0.81	0.59
Month×Year×Municipality FE	Yes	Yes
Controls	Yes	Yes
Mean	1.22	0.51

Notes: This table presents separate PPML estimates for the day (07:00–19:00) and night (19:00–07:00) periods. Estimation sample sizes differ because the PPML drops singletons and observations separated by fixed effects. All specifications include temperature-bin and precipitation controls. Mean denotes the mean outcome in the corresponding estimation sample. Standard errors, reported in parentheses, are clustered at the municipality level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

7 Conclusion

Wildfires are becoming an increasingly important source of air pollution, with smoke reaching populations far from the fire line. This paper examines how wildfire smoke affects road safety using municipality-day accident records from Alberta combined with satellite-based smoke maps. I find a nonlinear relationship between smoke exposure and traffic accidents: accident counts increase on light- and medium-smoke days but decline on heavy-smoke days.

Supplementary evidence from traffic counts suggests that reductions in driving during severe smoke events may help explain the decline in accidents under heavy smoke. In contrast, traffic volumes do not decline during light smoke exposure, even as accident counts increase. The visibility analysis suggests that reduced visibility alone is unlikely to explain this increase, although the underlying mechanisms cannot be definitively identified.

These findings highlight a potentially overlooked cost of wildfire smoke exposure and suggest that road safety risks may arise even during relatively mild smoke events. As wildfires intensify with climate change, better communication of these risks could help drivers make more informed decisions about travel during smoky conditions.

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Appendix 1

Table 11: Effect of Smoke Exposure on Traffic Accidents: Urban vs. Rural

	Urban	**Urban (PPML Sample)**	**Rural**	**Rural (PPML Sample)**
Light Smoke	0.024*	0.049*	0.004	0.004
	(0.014)	(0.029)	(0.010)	(0.010)
Medium Smoke	0.137	0.252	0.031	0.032
	(0.094)	(0.171)	(0.029)	(0.029)
Heavy Smoke	-0.016*	-0.036*	-0.068***	-0.070***
	(0.010)	(0.021)	(0.020)	(0.021)
Observations	311,696	149,713	100,464	98,438
R^2	0.9377	0.9368	0.5084	0.5048
Month×Year×Municipality FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Mean	0.98	2.05	0.86	0.88

Notes: This table presents OLS estimates using. Standard errors are clustered at the municipality level. Urban samples include cities, towns, villages, and summer villages. The PPML sample columns restrict the OLS regressions to the estimation sample used by PPML. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 12: 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	0.027	0.044	0.005	0.009
	(0.019)	(0.031)	(0.006)	(0.009)
Medium Smoke	0.096*	0.132*	0.050	0.043
	(0.054)	(0.075)	(0.037)	(0.037)
Heavy Smoke	-0.008	-0.017	-0.050**	-0.086**
	(0.013)	(0.021)	(0.024)	(0.040)
Observations	235,520	143,360	176,640	104,791
R^2	0.9325	0.9319	0.9367	0.9360
Month×Year×Municipality FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Mean	1.06	1.75	0.81	1.35

Notes: This table reports OLS estimates. Standard errors are clustered at the municipality level. The PPML sample columns restrict the OLS regressions to the estimation sample used in PPML. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 13: Effect of Smoke Exposure on Traffic Accidents by Collision Severity

	Fatal	Fatal (Main Specification Sample)	Injury	Injury (Main Specification Sample)	Property Damage	Property Damage (Main Specification Sample)
Light Smoke	-0.0000	-0.0001	0.0033	0.0092	0.0153*	0.0257*
	(0.0002)	(0.0042)	(0.0027)	(0.0074)	(0.0087)	(0.0146)
Medium Smoke	0.0024	0.0162	-0.0037	-0.0081	0.0825*	0.1026*
	(0.0017)	(0.0124)	(0.0083)	(0.0139)	(0.0465)	(0.0586)
Heavy Smoke	-0.0003	-0.0065	-0.0056**	-0.0168**	-0.0224***	-0.0409***
	(0.0003)	(0.0056)	(0.0027)	(0.0078)	(0.0085)	(0.0154)
Observations	412,160	23,778	412,160	147,675	412,160	244,531
R^2	0.0508	0.0135	0.7475	0.7377	0.9320	0.9313
Month×Year×Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean	0.00	0.04	0.10	0.28	0.85	1.43

Notes: This table reports OLS estimates using month×municipality fixed effects. Standard errors are clustered at the municipality level. The PPML sample columns correspond to the estimation sample used after accounting for separation and fixed effects. Temperature bins and precipitation are included as controls. Significance level: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 14: Effect of Smoke Exposure on Traffic Accidents (Urban vs. Rural)

	Urban	Urban (Main Specification Sample)	Rural	Rural (Main Specification Sample)
Light Smoke	0.0216***	0.0215***	0.0125	0.0126
	(0.0081)	(0.0081)	(0.0097)	(0.0098)
Medium Smoke	0.0255***	0.0259***	0.0477	0.0484
	(0.0093)	(0.0093)	(0.0326)	(0.0327)
Heavy Smoke	-0.0284***	-0.0285***	-0.0607***	-0.0600***
	(0.0075)	(0.0075)	(0.0199)	(0.0199)
Observations	202,297	149,713	100,280	98,438
Pseudo R^2	0.8943	0.8855	0.2800	0.2724
Month×Municipality FE	Yes	Yes	Yes	Yes
Year×Municipality FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Mean	1.51	2.05	0.86	0.88

Notes: This table reports PPML estimates using month×municipality and year×municipality fixed effects. Standard errors are clustered at the municipality level. The PPML sample columns correspond to the estimation sample used after accounting for separation and fixed effects. Temperature bins and precipitation are included as controls. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 15: Effect of Smoke Exposure on Traffic Accidents: Pre- vs. Post-COVID

	Pre-COVID	**Pre-COVID (Main Specification Sample)**	**Post-COVID**	**Post-COVID (Main Specification Sample)**
Light Smoke	0.025***	0.025***	-0.018	-0.018
	(0.006)	(0.006)	(0.013)	(0.013)
Medium Smoke	0.059***	0.059***	0.004	0.004
	(0.015)	(0.015)	(0.027)	(0.027)
Heavy Smoke	-0.021*	-0.021*	-0.079***	-0.080***
	(0.012)	(0.012)	(0.009)	(0.009)
Observations	165,757	143,360	120,705	104,791
Pseudo R^2	0.8309	0.8232	0.7983	0.7895
Month×Municipality FE	Yes	Yes	Yes	Yes
Year×Municipality FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Mean	1.51	1.75	1.18	1.36

Notes: This table reports PPML estimates using month×municipality and year×municipality fixed effects. Standard errors are clustered at the municipality level. The PPML sample columns correspond to the estimation sample used after accounting for separation and fixed effects. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

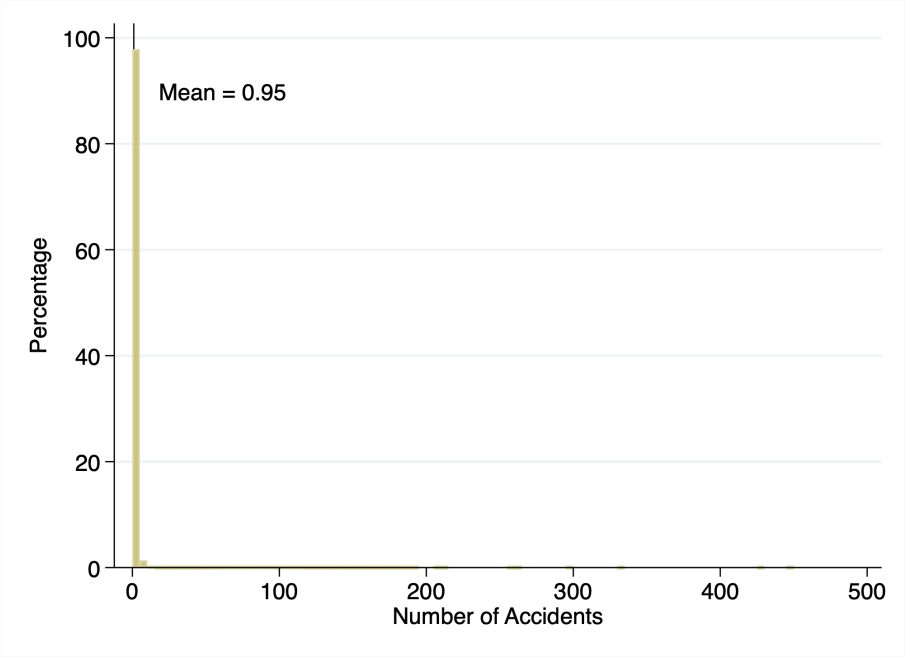
Table 16: Effect of Smoke Exposure on Traffic Accidents by Collision Severity (PPML)

	Fatal	**Fatal (Main Specification Sample)**	**Injury**	**Injury (Main Specification Sample)**	**Property Damage**	**Property Damage (Main Specification Sample)**
Light Smoke	0.0083	-0.0011	0.0379**	0.0378**	0.0171***	0.0171***
	(0.0915)	(0.0954)	(0.0158)	(0.0157)	(0.0066)	(0.0066)
Medium Smoke	0.3652*	0.3358	-0.0172	-0.0116	0.0394***	0.0398***
	(0.2051)	(0.2141)	(0.0461)	(0.0474)	(0.0131)	(0.0131)
Heavy Smoke	-0.1192	-0.1033	-0.0552***	-0.0514***	-0.0324***	-0.0322***
	(0.1225)	(0.1258)	(0.0185)	(0.0181)	(0.0074)	(0.0074)
Observations	57,009	23,778	200,447	147,675	299,078	244,531
Pseudo R^2	0.0669	0.0213	0.5219	0.4846	0.8186	0.8075
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	0.02	0.04	0.21	0.28	1.17	1.43

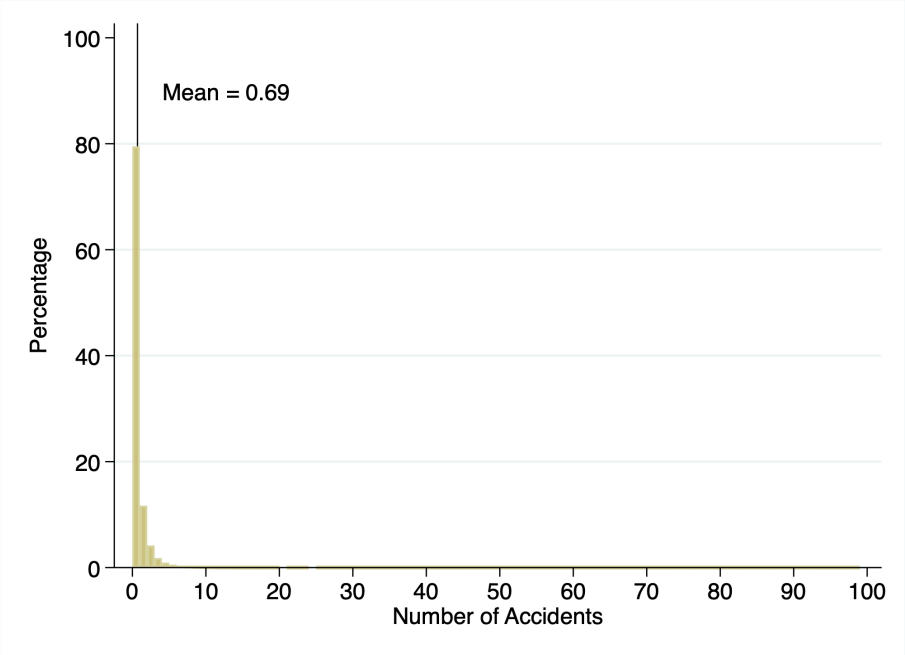
Notes: This table reports PPML estimates using month×municipality and year×municipality fixed effects. Standard errors are clustered at the municipality level. The PPML sample columns correspond to the estimation sample used after accounting for separation and fixed effects. Temperature bins and precipitation are included as controls. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendix 2

Figure 1: Distribution of Accidents

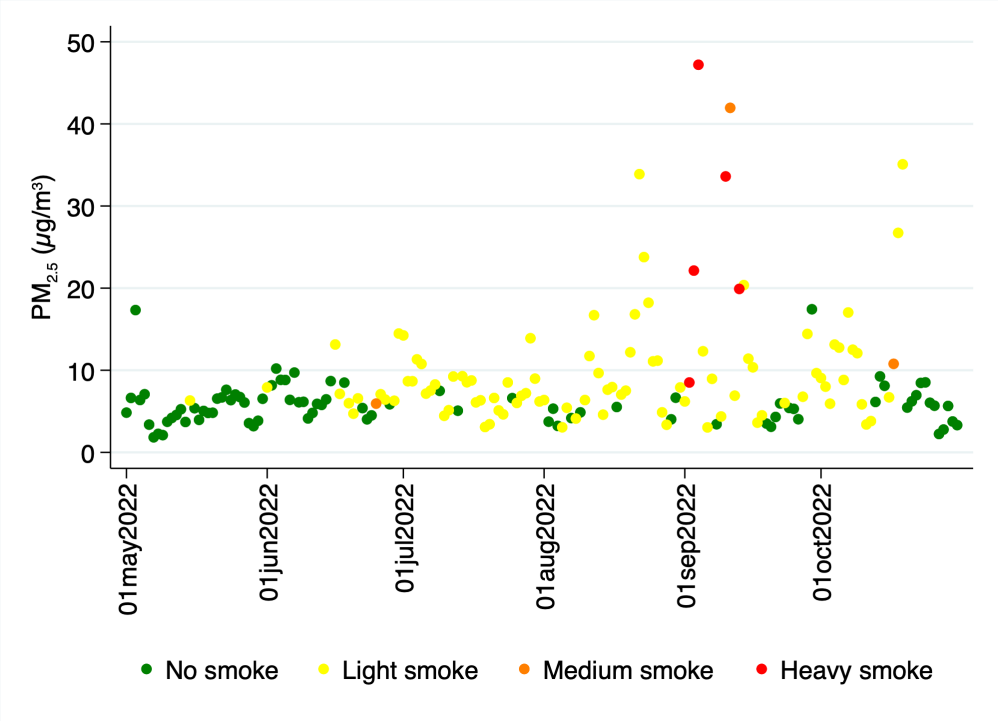


(a) Distribution of daily municipality-level accidents, full sample



(b) Distribution of daily municipality-level accidents, days with fewer than 100 accidents

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

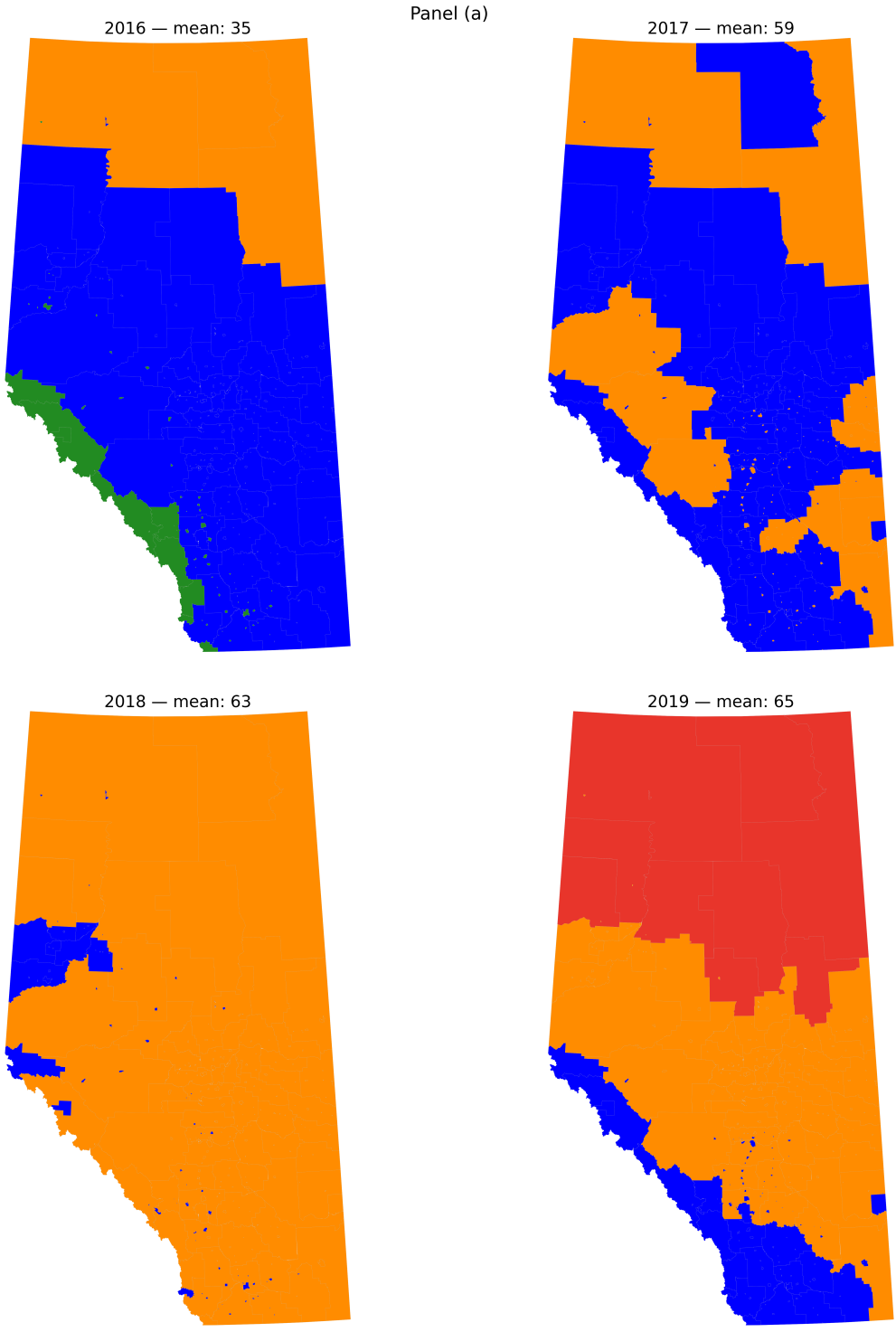
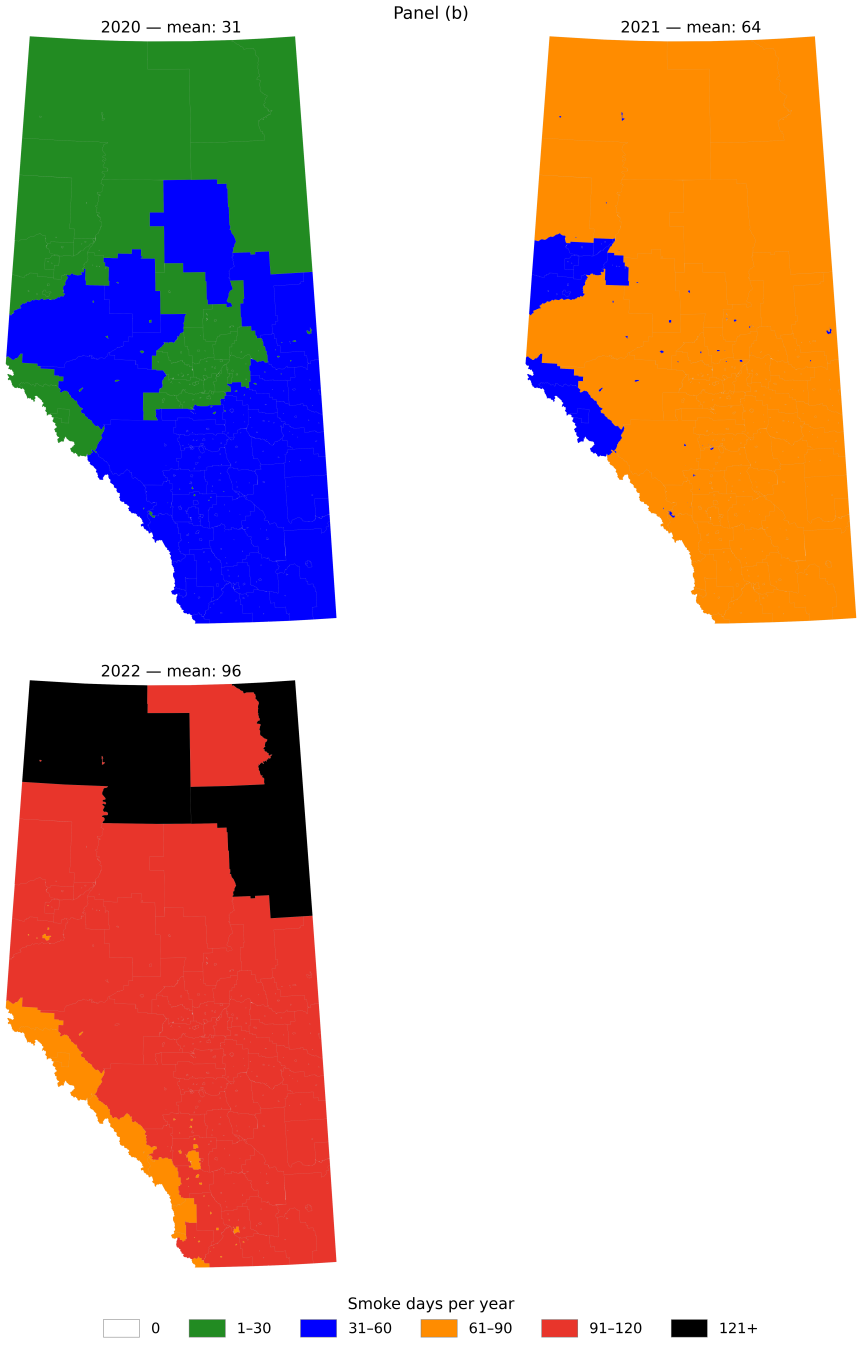


Figure 3: Yearly Number of Smoke Days in Municipalities in Alberta (continued)



Note: This figure shows the annual count of smoke days of any intensity across the municipalities of Alberta over 2016–2022. Panel (a) covers the first four years and panel (b) the remaining three. The legend in panel (b) applies to both panels.