How extreme heat and poor air quality impact healthcare utilization among insured Californians

Jointly prepared by Milliman and Blue Shield of California

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1. Executive summary

Climate change poses a significant threat to human health.[1] Global temperatures continue to rise, driving increasingly frequent extreme weather events, such as storms and floods. Beyond acute events and impacts, the effects of climate change also have significant chronic impacts on human health, leading to an increase in illness, mental health issues, and death.[2] Climate change is one of various environmental determinants of health—responsible for between 25% and 33% of global disease—which play a role in determining how, when, and to what extent individuals seek and receive healthcare.[3]

Exposure to extreme heat and poor air quality increases the risk of several medical conditions,[4] both acute and chronic. These range from heat stroke and asthma attacks to chronic obstructive pulmonary disease (COPD) complications, lung cancer, and increased risk of premature birth. Vulnerable populations are particularly susceptible to experiencing more severe health impacts from climate events.

In recent years, Californians have encountered frequent extreme heat and air pollution events.[5] There has been limited research about how these events impact healthcare utilization and how they intersect with social determinants of health (SDOH). Blue Shield of California collaborated with Milliman, Inc. to investigate the impact of two environmental factors—extreme heat and poor air quality—on healthcare utilization among the insured population in California in the years 2017–2019.

This research yielded several key insights:

1. Extreme heat and poor air quality had statistically significant impacts on healthcare utilization.

   From 2017–2019, both factors were associated with statistically significant fluctuations across the six measures of healthcare utilization studied: medical admissions, emergency department (ED) visits, urgent care visits, observational stays (without ED), primary care physician (PCP) visits, and specialist visits.

2. Extreme heat and poor air quality were associated with increased but also *decreased* healthcare utilization. Extreme heat had a relatively modest impact on healthcare utilization, while poor air quality had a more significant effect.

   Extreme heat and poor air quality were associated with both higher *and* lower healthcare utilization depending on the healthcare utilization metric and the characteristics of the subpopulations being examined.

   - **Poor air quality** was linked to higher rates of respiratory conditions like asthma attacks, COPD complications, and lung infections. In our analysis, it was associated with up to +/-25 additional healthcare visits for every 1,000 individuals, but for some populations up to 117 additional visits per 1,000.

1. Hsu, S., Moskeland, A., Palmeiro-Silva, Y., Romanello, M., Scamman, D., Walawender, M., et al. (November 9, 2024). The 2024 report of the Lancet Countdown on health and climate change: facing record-breaking threats from delayed action. The Lancet, 404(10465), 1847–96. Retrieved March 20, 2025, from https://lancetcountdown.org/2024-report/#:~:text=The%20latest%20Lancet%20Countdown%20report,action%20to%20protect%20health%20persist.

2. Hsu, S., Moskeland, A., Palmeiro-Silva, Y., Romanello, M., Scamman, D., Walawender, M., et al. (November 9, 2024). The 2024 report of the Lancet Countdown on health and climate change: facing record-breaking threats from delayed action, ibid.

3. Corvalán, C.F., Kjellström, T., & Smith, K.R. (September 1999). How much global ill health is attributable to environmental factors? Epidemiology, 10(5), 573–84. Retrieved March 20, 2025, from https://pubmed.ncbi.nlm.nih.gov/10468437/.

4. Office of Environmental Health Hazard Assessment (OEHHA). (November 2025). Indicators of Climate Change in California, Fourth Edition, California Environmental Protection Agency, OEHHA. Retrieved March 20, 2025, from https://oehha.ca.gov/media/downloads/climate-change/document/2022caindicatorsreport.pdf.

5. Smith, H. (July 2, 2024). The toll of extreme heat rises in California as OSHA advances worker protections. Los Angeles Times. Retrieved March 20, 2025, from https://www.latimes.com/environment/story/2024-07-02/the-toll-of-extreme-heat-is-rising-in-california.

  - **Extreme heat** can cause dehydration, heat stroke, and cardiovascular stress. In our analysis, it was associated with +\-5 counts of healthcare visits per 1,000 individuals.

  The underlying reasons for the difference in magnitude between extreme heat and air pollution are likely multifaceted. Hypotheses include:

  - **Differences in awareness and perceived risk** about the impacts of poor air quality compared to extreme heat may have influenced the degree of preparedness and adoption of coping mechanisms for poor air quality compared to extreme heat, both at the individual and community levels.
  - **Variations in the ability to mitigate** these issues. For example, study participants may have more effective means to combat extreme heat than to protect against poor air quality.
  - **Socio-economic status may be a factor as well.** Air conditioning and cooling centers might be more accessible to a broader section of the population, whereas high-quality air purification systems might be less accessible.

3. The effects persisted for weeks to months, with utilization varying across different population groups.

   The study monitored effects up to three months after an index event of extreme heat or air pollution, observing effects that emerged and/or lasted for weeks to months. Air quality had a faster impact on utilization, with impacts manifesting more immediately than extreme heat. The impact of extreme heat on healthcare utilization was found to be more pronounced after a delay of two to three months. While elevated cardiovascular stress and acute cardiovascular events are the primary health concern of extreme heat, dehydration can exacerbate existing chronic conditions such as kidney disease which may contribute to the delayed utilization.

4. The interaction among extreme heat, poor air quality, individual health status, and SDOH is intricate and varied.

   Extreme heat and poor air quality led to either higher or lower healthcare utilization depending on the utilization metric being examined. For example, when considering ozone—one of three types of air pollution studied—and the percentage of people living in crowded housing units in the area, a 1% increase in crowded housing correlates with 100 more observational stays and 45 more specialist visits per 1,000, yet 30–32 per 1,000 fewer medical admissions, ED visits, and urgent care visits. This pattern differs when examining the effects of particulate matter 2.5 (PM2.5)—another type of air pollutant—where a 1% increase in crowded housing is associated with 18–20 per 1,000 more medical admissions and specialist visits, but 37 per 1,000 fewer ED visits and 97 per 1,000 fewer PCP visits.

Overall, this analysis illuminates the significant and nuanced ways in which extreme heat and poor air quality influence healthcare utilization. Climate change is exacerbating environmental events, introducing more complexity, variance, and unpredictability, which may cause particular concern for health plans that rely on predictability for financial forecasting and rate setting, as well as members who face health impacts and higher out-of-pocket cost. Healthcare utilization impacts are magnified geographically and by social need. Such findings may be valuable to both health plans and providers looking to address the needs of vulnerable populations, devise focused strategies to mitigate the health effects of environmental stressors, and understand and build resilient healthcare systems able to meet the complex and varying needs of populations increasingly impacted by environmental events.

2. Data

In this section, we describe the data sources used in our study.

2.1 HEALTHCARE CLAIMS DATA – MILLIMAN'S CONSOLIDATED HEALTH COST GUIDELINES SOURCES DATABASE (CHSD)

The Consolidated Health Cost Guidelines™ Sources Database (CHSD) is Milliman's proprietary and extensive healthcare claims database. It compiles longitudinal data from national and regional health plans, healthcare providers, and self-insured employers. This database encompasses multiple years and various lines of business, offering a comprehensive view of healthcare costs and utilization.

For our study, we selected the period from 2017–2019. This time frame was chosen to capture a period of relative stability following major healthcare reforms, yet prior to the disruptions caused by the COVID-19 pandemic. Our analysis focused on California residents who had at least 10 months of continuous medical and pharmacy coverage during this period.

In the CHSD, a method of de-identification is employed where adjacent counties are grouped together to form larger geographic entities. In this report, we refer to these entities as "super-counties." This approach ensures the privacy of individuals in the database while still providing valuable geographic insights for our analysis.

2.2 HEAT WAVES DATA

We utilized weather data from the National Oceanic and Atmospheric Administration's (NOAA's) National Centers for Environmental Information Local Climatological Data[6] (LCD) network and the National Interagency Fire Center's Remote Automatic Weather Station (RAWS) network.[7] Observations at LCD stations are recorded subhourly to hourly, while RAWS stations provide hourly data.

Our analysis involved downloading daily weather measurements from all LCD and RAWS stations across California. We focused on weather variables like mean air temperature and relative humidity during the summer months (May–September) for the years 1997–2022.

To maintain data quality, we applied standards similar to those used by the Environmental Protection Agency (EPA) in its heat wave calculations.[8] Stations were included in our analysis if they recorded data for 98% of valid months during the observation period. A month was deemed valid if data was available for at least 60% of its days (18 days for 30-day months and 19 days for 31-day months).

We identified heat waves using two methods: 1) periods of 2-plus days where daily minimum or maximum apparent temperatures at a station exceeded the 85th percentile of historical summer temperatures for the base period of 1997–2022, and 2) periods of 2-plus days where the daily minimum or maximum heat index surpassed the 95th percentile of historical summer heat indexes for the same base period.

Both apparent temperature and heat index, which combine humidity and temperature measurements, were calculated using formulas from the EPA and the National Weather Service, respectively.

6. National Centers for Environmental Information (NCEI). (n.d.). National Oceanic and Atmospheric Administration's (NOAA's) Local Climatological Data (LCD). Retrieved March 20, 2025, from https://www.ncei.noaa.gov/products/land-based-station/local-climatological-data.

7. National Interagency Fire Center (NIFC). (n.d.). Remote Automatic Weather Stations (RAWS). Retrieved March 20, 2025, from https://www.nifc.gov/about-us/what-is-nifc/remote-automatic-weather-stations.

8. Environmental Protection Agency (EPA) (June 2024). Technical Documentation: Heat Waves. Retrieved March 20, 2025, from https://www.epa.gov/system/files/documents/2024-06/heat-waves_documentation.pdf.

To align weather data with specific ZIP Codes, we located weather stations within 25 km of a ZIP Code's centroid. If no station was within this range, the nearest station was used. For each heat statistic (apparent temperature or heat index), we computed the inverse-distance weighted average from stations within 25 km or from the nearest station if no station was within this range. Each ZIP Code was then assigned a weighted average value for each heat statistic for all days.

This process yielded data indicating the start date; duration of heat waves; and the average, minimum, and maximum apparent temperatures or heat indexes for each day of a heat wave in every county code.

Finally, to merge this weather data with the CHSD data at the super-county level, we mapped ZIP Codes to their corresponding super-counties. We then calculated the counts and total duration of heat waves in each super-county for a given month, thereby providing a comprehensive view of heat wave occurrences and intensities at this larger geographic scale.

2.3 AIR QUALITY DATA

We utilized air quality data from the EPA's AirNow[9] monitoring network for our study. Due to challenges in data acquisition and validation, along with concerns about its comparability and consistency, we chose not to include data from the crowdsourced PurpleAir[10] monitoring network for this project. Future studies might benefit from integrating PurpleAir data.

Our data collection involved downloading the reported daily values from 1/1/2017 to 12/31/2019 from all AirNow monitoring sites. We focused on three pollutants: 24-hour average particulate matter 2.5 concentration (PM2.5-24hr), 24-hour average particulate matter 10 concentration (PM10-24hr), and 8-hour average maximum ozone concentration (Ozone-8hr). It's important to note that not all monitoring sites report each of these pollutants, and data availability varied by day.

We then attributed this daily air quality data to each ZIP Code in California. For each county, we identified air monitoring sites within 25 km of the ZIP Code's centroid that reported each pollutant on a given day. If no monitoring sites for a specific pollutant were within this range, we selected the closest site that reported data for that day. We calculated the inverse-distance weighted average of the reported pollutant concentrations from all sites within 25 km (or the closest site if none were within this range). Each ZIP Code was then assigned a weighted average concentration value for each pollutant for all days.

The calculated concentration values for each pollutant in each ZIP Code were categorized as "Good," "Moderate," "Unhealthy for Sensitive Groups," "Unhealthy," "Very Unhealthy," or "Hazardous," following the concentration-to-category lookup table found in the Air Quality Index (AQI) technical documentation.[11] For modeling purposes, we only retained records where the air quality was categorized as other than "Good."

To integrate this data with the CHSD data at the super-county level, we mapped the ZIP Codes to their corresponding super-counties. We then calculated the total duration of poor air quality as indicated by PM2.5, PM10, and Ozone levels for each month at the super-county level. This process allowed us to effectively analyze the impact of air quality on healthcare utilization within these larger geographic areas.

9. Environmental Protection Agency (EPA). (n.d.) AirNow.gov. Retrieved March 20, 2025, from https://www.airnow.gov.

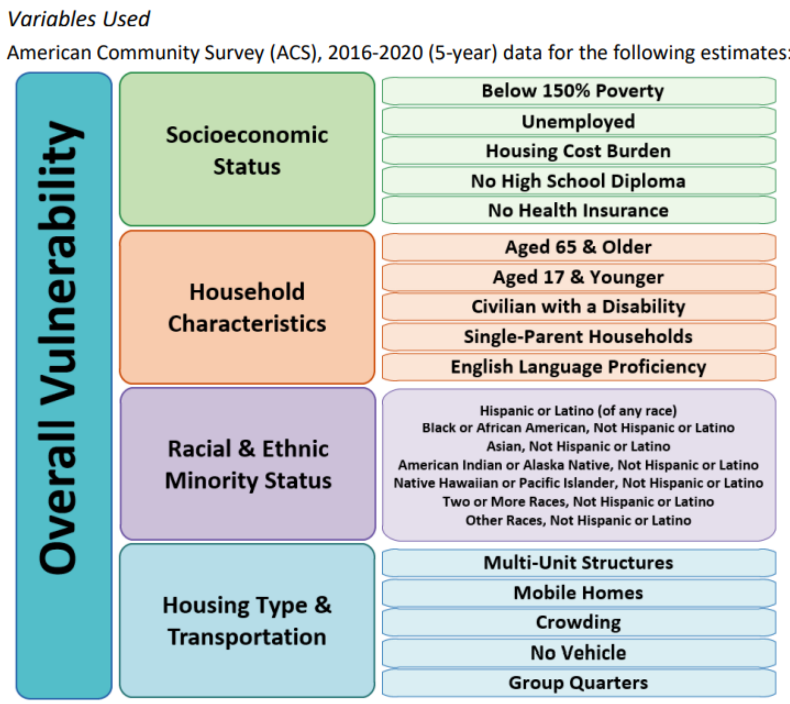
10. More information about PurpleAir is available at https://www2.purpleair.com.

11. U.S. Environmental Protection Agency (EPA). (September 2018). Technical Assistance Document for the Reporting of Daily Air Quality – the Air Quality Index (AQI). Retrieved March 20, 2025, from https://www.airnow.gov/sites/default/files/2020-05/aqi-technical-assistance-document-sept2018.pdf.

2.4 SOCIAL DETERMINANTS OF HEALTH DATA

Socioeconomic factors have been found to have significant impacts on healthcare cost, utilization, and health outcomes in recent years.[12] The Centers for Disease Control and Prevention (CDC) Social Vulnerability Index (SVI)[13] is a tool designed to assess and measure the vulnerability of communities in the presence of external stresses on human health. It includes 16 census measures that fall into four distinct categories:[14]

FIGURE 1: CDC'S SOCIAL VULNERABILITY INDEX (SVI)
VARIABLES USED, FOUR CATEGORIES



In order to merge with the CHSD data at the super-county level, we took the 16 county-level individual measures in the SVI and recalculated at the super-county level.

12. U.S. Department of Health and Human Services, Office of Disease Prevention and Health Promotion. (n.d.) Social Determinants of Health Literature Summaries - Healthy People 2030. Retrieved March 20, 2025, from https://health.gov/healthypeople/priority-areas/social-determinants-health/literature-summaries.

13. Agency for Toxic Substances and Disease Registry (ATSDR). (July 22, 2024). Place and Health - Geospatial Research, Analysis, and Services Program (GRASP) Social Vulnerability Index. Retrieved March 20, 2025, from https://www.atsdr.cdc.gov/place-health/php/svi/?CDC_AAref_Val=https://www.atsdr.cdc.gov/placeandhealth/svi/.

14. Agency for Toxic Substances and Disease Registry (ATSDR). (August 5, 2022). CDC/ATSDR SVI 2020 Documentation. CDC. Retrieved March 20, 2025, from https://www.atsdr.cdc.gov/placeandhealth/svi/documentation/pdf/SVI2020Documentation_08.05.22.pdf.

3. Methodology

In this section, we describe the methodology used in our study.

3.1 HEALTHCARE UTILIZATION METRICS MODELED

We selected six (6) healthcare utilization measures to model the impact of extreme heat and poor air quality, including:

- Medical admissions
- ED visits
- Urgent care visit counts
- Observational stays without ED
- PCP visits
- Specialist visits

They were calculated on the California portion of the CHSD using the Milliman Health Cost Guidelines (HCG)[15] grouping methodology and represent healthcare services from all causes, not just heat-related causes.[16]

3.2 RISK ADJUSTMENT

In health services research, relative risk scores are a common tool for quantifying an individual's health risks compared to the general population. These scores are derived from healthcare claims data, considering factors like age, gender/sex, and medical and prescription drug history. Calculated at the individual level, these scores are then aggregated. A relative risk score of 1.0 suggests that the individual is expected to utilize an average amount of healthcare resources compared to a reference population. In contrast, a score of 1.5 indicates that the individual is likely to consume 1.5 times the average healthcare resources of the reference population.

For our project, we utilized the Centers for Medicare and Medicaid Services (CMS) hierarchical condition category (HCC)[17] community relative risk scores for the Medicare segment of the population and the Department of Health and Human Services (HHS) HCC[18] for the platinum metal level relative risk scores for the non-Medicare segment.

While risk scores are designed to accurately predict healthcare spending at the population level, their precision can vary at the individual or subpopulation level. This potential imprecision in risk adjustment might affect the modeling results, especially when including the risk score as an explanatory variable to estimate the impacts of extreme heat and air pollution on healthcare utilization.

3.3 DATA SUMMARIZATION AND MERGE

In the preceding section, we described various types of data that we aggregated for our analysis. This included daily healthcare utilization data at the individual level, daily measures of extreme heat and air pollution by geographic area, annually varying individual-level risk scores, and 16 SDOH measures, captured as yearly snapshots and varying by geography. The unifying element across all these data features is the concept of a “super-county.”

15. Milliman. (2025). Health Cost Guidelines. Retrieved March 20, 2025, from https://www.milliman.com/en/products/health-cost-guidelines-suite.

16. Milliman. (2025). Health Cost Guidelines – Grouper. Retrieved March 20, 2025, from https://us.milliman.com/en/products/hcggrouper.

17. Centers for Medicare and Medicaid Services (CMS). (October 24, 2024). Risk Adjustment. Retrieved March 20, 2025, from https://www.cms.gov/medicare/payment/medicare-advantage-rates-statistics/risk-adjustment.

18. Cohen, M., Freeman, S., Ingber, M., Kautter, J., Keenan, P., Patterson, L., & Pope, G.C. (2014). The HHS-HCC Risk Adjustment Model for Individual and Small Group Markets under the Affordable Care Act. Medicare & Medicaid Research Review, 4(3). Retrieved March 20, 2025, from https://www.cms.gov/mmrr/articles/a2014/mmrr2014_004_03_a03.html.

To facilitate our analysis, we summarized the daily variables on a monthly basis, covering the period from January 2017 to December 2019. Following this, we merged all the data features by super-county, enabling a comprehensive and geographically contextual analysis of the impacts of healthcare utilization, environmental factors, risk scores, and SDOH measures.

3.4 MODELING

Each utilization metric has its own model. The function below describes the conceptual modeling framework.

$$\boldsymbol{U^t = F\left(A^t, S, L, R, P^t, P^{lag}, I^t, I^{lag}\right)},$$

Where:

- U^t is the utilization count in month t.
- $\boldsymbol{A^t}$ is the age-gender composition of the population in month t.
- $\boldsymbol{S}$ is a vector of 16 SDOH census measures of the population, based on the geographic location of the population at the start of a calendar year.
- $\boldsymbol{L}$ is line of business mix of the population.
- $\boldsymbol{R}$ is the risk score.
- $\boldsymbol{P^t}$ represents a vector that measures extreme heat and air pollution in month t, including the duration, frequency, and severity of these climate events.
- $\boldsymbol{P^{lag}}$ represents a set of variables that measure extreme heat and air pollution from prior months.
- $\boldsymbol{I^t}$ represents a set of interaction variables to capture the interplay between demographics, risk scores, SDOH, and the climate events in month t.
- $\boldsymbol{I^{lag}}$ represents a set of interaction variables to capture the interplay between demographics, risk scores, SDOH, and the climate events from prior months.

Best practices in model development prioritize a balance among accuracy, efficiency, complexity, suitability, and interpretability. In our approach, we utilized machine learning techniques to identify key drivers of healthcare cost and utilization. This process involved exploring complex interactions among various factors, a step known as "feature engineering."

Subsequently, we developed generalized linear models (GLMs) with a linear link function. These models were specifically designed to estimate the direction and magnitude of significant risk drivers. Each model incorporated over 170 explanatory variables, including time lags of zero, one, two, and three months. This was to examine whether occurrences of extreme heat and air pollution in a given month could influence healthcare utilization in subsequent months.

An integral part of our modeling process was testing for collinearity among the risk drivers. This step is crucial to ensure the robustness of the models, as it helps in verifying that the explanatory variables are independent and do not unduly influence each other. This careful approach in model construction aims to yield accurate, efficient, and interpretable results, aligning with the best practices in model development.

4. Results

In this section, we describe and discuss the results and implications in our study.

4.1 MAGNITUDE AND STATISTICAL SIGNIFICANCE

We chose a linear (normal distribution) link function for the GLMs so that the coefficients can be interpreted as the change in utilization counts for a one-unit change in the explanatory variable, holding all other explanatory variables constant. The coefficients from the GLMs are included in Figure 2 and are all significant at 0.05 level. Given that most of them are quite small, for purpose of discussion and ease of interpretation, we added a column, "Estimate x 1,000," to magnify the size of the coefficients so that they may be discussed in terms of per 1,000 members. For example, in the urgent care visits model, the coefficient associated with "HW 0 lag x RS x %unemployment" (the interaction of total days of extreme heat in current month, risk score, and the percent of unemployment in the super-county) is 0.005025.[19] Multiplying this by 1,000, we get 5.025, meaning, for one unit increase in the interaction variable "HW 0 lag x RS x %unemployment," an increase in urgent care visits of 5.025 is expected per 1,000 members. To improve readability, we used conditional formatting in this figure. Positive coefficients are in red cells of various intensity, and negative coefficients are in green cells of various intensity. A higher intensity indicates a larger magnitude.

Overall, we find the influence of extreme heat, while statistically significant, is relatively modest in its magnitude. Most coefficients associated with extreme heat and its interactions are less than +/- 5 per 1,000 members. This suggests that for every 1,000 individuals, there is an increase or decrease in healthcare utilization by about 5 counts due to extreme heat.

In contrast, there is a more substantial association between poor air quality and healthcare utilization. Many coefficients related to poor air quality fall in the +/- 25 per 1,000 members range, and some even reach more than +/- 100 per 1,000 members.

The underlying reasons for this notable difference could be multifaceted. One plausible explanation revolves around the relative effectiveness of mitigation strategies available to individuals for coping with these environmental factors. It could be that poor air quality, particularly during this time period of study from 2017–2019, did not draw awareness in the same ways as extreme heat. It is also possible that Californians, as represented in the study, may have more effective means to combat extreme heat than to protect against poor air quality. The widespread availability and use of air conditioning systems, along with community cooling centers, provide effective relief from heat, thus mitigating its impact on health and subsequent healthcare utilization. On the other hand, protections against poor air quality, such as air purifiers, may not be as widely known about, accessible, or effective. Air pollutants can permeate indoor environments, and the efficacy of air purifiers can vary significantly based on factors like the type of pollutant, the size of the space, and the quality of the air purifier itself. Moreover, the insidious nature of air pollution, which can exacerbate a range of respiratory and cardiovascular conditions, might make it a more potent factor in driving healthcare utilization. Furthermore, there could be socioeconomic factors at play. Air conditioning and cooling centers might be more accessible to a broader section of the population, whereas high-quality air purification systems might be a luxury unaffordable to many in need. This difference in accessibility could contribute to the observed disparity in the impact of these two environmental factors on healthcare utilization.

19. Digits after the third place are not shown in Figure 2.

FIGURE 2: GENERALIZED LINEAR MODELS, PREDICTING HEALTHCARE UTILIZATION COUNTS
MODEL COEFFICIENTS

		Effect (Explanatory Variables)	Medical Admissions Estimate	Medical Admissions Estimate x 1,000	ED Visits Estimate	ED Visits Estimate x 1,000	Urgent Care Visits Estimate	Urgent Care Visits Estimate x 1,000	Observational Stays Without ED Estimate	Observational Stays Without ED Estimate x 1,000	PCP Visits Estimate	PCP Visits Estimate x 1,000	Specialist Visits Estimate	Specialist Visits Estimate x 1,000
		Intercept	-6.061		-4.729		-4.744		-8.627		-5.376		-3.004	
Coverage Type		LOB - Medicare Advantage	1.602		-0.060		0.584		1.377		3.094		1.014	
		LOB - Medicare ACOs	1.228		-0.055		0.869		1.101		3.746		1.193	
		LOB - Commercial	-0.809		-0.938		0.843		0.429		2.285		-0.298	
		LOB - Other (reference group)	0.000		0.000		0.000		0.000		0.000		0.000	
Seasonality		month - Jan	-0.189		-0.041		-0.018		-0.067		0.185		0.031	
		month - Feb	-0.264		-0.094		-0.171		-0.060		0.024		0.008	
		month - Mar	-0.158		0.006		-0.091		-0.055		0.098		0.133	
		month - Apr	-0.225		-0.134		-0.209		-0.136		-0.013		0.066	
		month - May	-0.177		-0.117		-0.223		-0.098		0.000		0.102	
		month - Jun	-0.229		-0.193		-0.287		-0.031		-0.028		0.032	
		month - Jul	-0.145		-0.149		-0.209		-0.117		-0.040		0.028	
		month - Aug	-0.160		-0.181		-0.239		-0.020		-0.017		0.115	
		month - Sept	-0.154		-0.093		-0.243		0.008		-0.026		0.093	
		month - Oct	-0.085		-0.081		-0.259		0.086		0.075		0.208	
		month - Nov	-0.080		-0.136		-0.205		0.024		-0.056		0.015	
		month - Dec (reference group)	0.000		0.000		0.000		0.000		0.000		0.000	
Health Status	Direct Effect	RiskScore (RS)	0.906		1.227		0.411		2.760		5.968		-1.010	
	Interaction Effect	RS x %unemployment	26.819		26.690		67.296		-17.467		-29.840		20.255	
		RS x %w limited English language capabilities	3.349		-1.407		14.434		17.718		31.244		-9.671	
		RS x %identified as nonwhite	-1.691		-1.722		-5.186		-2.197		-4.146		0.503	
		RS x %uninsured	1.835		-11.675		9.208		-0.740		-13.128		7.878	
		RS x %living in mobile homes	-17.823		-28.097		-15.438		-21.843		-61.712		13.749	
		RS x %living in crowded housing units	-15.636		34.613		-34.075		-77.089		-82.307		19.408	
		RS x %without vehicle	-17.585		10.180		-9.681		-9.218		-14.131		6.885	
		RS x %living in group quarters	2.949		0.634		-7.033		3.006		-27.806		8.176	
Current month's heatwave	Direct Effect	Current HW days (HW 0 Lag)	0.000	0.001	0.000	0.000	0.000	0.007	0.000	0.006	0.000	-0.002	0.000	0.004
	Interaction effect	HW 0 lag x RS x %unemployment	0.000	-0.410	-0.001	-1.270	0.005	5.025	0.001	1.201	0.002	1.851	-0.003	-2.820
		HW 0 lag x RS x %w limited English language capabilities	0.000	0.412	-0.001	-0.870	0.000	-0.330	0.001	0.605	-0.001	-1.110	0.000	0.221
		HW 0 lag x RS x %identified as nonwhite	0.000	0.186	0.000	0.411	0.000	-0.480	0.000	0.101	0.000	0.008	0.001	0.580
		HW 0 lag x RS x %uninsured	0.000	0.161	-0.001	-0.890	0.000	0.241	0.000	-0.001	0.000	-0.490	0.000	-0.070
		HW 0 lag x RS x %living in mobile homes	-0.002	-1.880	-0.006	-5.970	0.001	1.056	-0.002	-1.790	-0.002	-2.440	-0.004	-4.410
		HW 0 lag x RS x %living in crowded housing units	-0.004	-3.600	0.000	-0.470	0.005	5.474	-0.006	-5.650	0.003	3.325	-0.008	-7.630
		HW 0 lag x RS x %without vehicle	-0.002	-2.040	-0.002	-1.970	0.000	0.493	0.001	0.934	0.000	0.460	-0.002	-2.420
		HW 0 lag x RS x %living in group quarters	0.001	0.624	0.003	2.526	-0.002	-2.060	0.000	-0.130	0.000	-0.110	0.001	1.458
Previous month's heatwave	Direct Effect	Heatwave days 1 month ago (HW 1 Lag)	0.000	0.006	0.000	0.002	0.000	0.007	0.000	0.008	0.000	-0.003	0.000	0.005
	Interaction effect	HW 1 lag x RS x %unemployment	-0.001	-0.730	-0.001	-0.530	0.003	2.969	0.006	6.368	0.004	4.450	-0.001	-0.620
		HW 1 lag x RS x %w limited English language capabilities	0.001	0.506	-0.001	-0.590	0.001	1.106	-0.002	-2.280	-0.002	-2.040	0.000	0.388
		HW 1 lag x RS x %identified as nonwhite	0.000	-0.180	0.000	-0.030	0.000	-0.170	0.000	0.193	0.000	0.075	0.000	-0.100
		HW 1 lag x RS x %uninsured	0.000	0.229	-0.001	-0.530	0.001	0.685	-0.003	-3.280	0.000	-0.480	0.000	0.277
		HW 1 lag x RS x %living in mobile homes	0.003	3.203	-0.001	-0.520	0.001	0.695	-0.015	-15.450	-0.005	-5.300	0.002	2.197
		HW 1 lag x RS x %living in crowded housing units	0.000	0.166	0.003	3.351	-0.005	-4.910	0.007	7.479	0.005	4.848	0.000	-0.060
		HW 1 lag x RS x %without vehicle	0.002	1.628	0.001	0.847	0.001	0.584	-0.002	-1.900	-0.001	-1.070	0.000	0.357
		HW 1 lag x RS x %living in group quarters	0.000	-0.270	0.001	1.020	-0.002	-1.650	0.005	5.469	-0.001	-1.110	0.000	-0.360
Previous 2 months' heatwave	Direct Effect	Heatwave days 2 months ago (HW 2 Lag)	0.000	0.005	0.000	0.000	0.000	0.001	0.000	0.008	0.000	-0.002	0.000	0.003
	Interaction effect	HW 2 lag x RS x %unemployment	0.002	1.711	0.002	1.788	0.001	0.710	-0.001	-0.550	0.002	2.072	0.000	0.404
		HW 2 lag x RS x %w limited English language capabilities	0.001	1.199	-0.001	-0.550	0.002	2.178	-0.001	-1.250	-0.001	-0.740	0.000	0.077
		HW 2 lag x RS x %identified as nonwhite	0.000	-0.180	0.000	-0.080	0.000	0.098	0.000	0.240	0.000	0.040	0.000	0.032
		HW 2 lag x RS x %uninsured	0.001	0.771	0.000	0.160	0.001	0.980	-0.001	-0.550	0.000	-0.010	0.000	0.212
		HW 2 lag x RS x %living in mobile homes	0.002	2.427	0.000	-0.060	0.000	-0.310	-0.003	-3.380	-0.002	-2.070	0.000	-0.020
		HW 2 lag x RS x %living in crowded housing units	-0.004	-3.620	0.003	2.509	-0.011	-10.900	0.001	1.123	0.001	1.155	-0.001	-0.900
		HW 2 lag x RS x %without vehicle	0.000	-0.340	-0.001	-0.660	-0.002	-1.780	0.000	0.380	-0.001	-0.660	-0.001	-0.900
		HW 2 lag x RS x %living in group quarters	-0.002	-1.530	-0.001	-1.270	0.000	-0.480	0.001	0.627	-0.001	-0.860	-0.001	-0.700
Previous 3 months' heatwave	Direct Effect	Heatwave days 3 months ago (HW 3 Lag)	0.000	0.002	0.000	-0.004	0.000	0.002	0.000	0.006	0.000	-0.002	0.000	-0.001
	Interaction effect	HW 3 lag x RS x %unemployment	-0.001	-1.290	-0.001	-0.860	0.005	5.066	0.010	9.750	0.001	1.345	-0.002	-1.770
		HW 3 lag x RS x %w limited English language capabilities	-0.001	-0.510	-0.001	-0.880	0.000	-0.040	-0.001	-0.670	-0.001	-0.860	0.000	-0.370
		HW 3 lag x RS x %identified as nonwhite	0.000	0.272	0.000	0.181	-0.001	-0.660	-0.001	-0.850	0.000	0.131	0.000	0.239
		HW 3 lag x RS x %uninsured	0.000	-0.130	-0.001	-0.730	0.000	-0.080	-0.001	-0.540	-0.001	-0.640	0.000	0.153
		HW 3 lag x RS x %living in mobile homes	-0.002	-1.890	-0.003	-2.840	0.003	2.830	0.001	0.750	-0.004	-3.550	-0.001	-0.510
		HW 3 lag x RS x %living in crowded housing units	-0.001	-1.180	0.002	2.365	0.007	7.220	0.010	10.360	0.001	0.956	-0.001	-1.220
		HW 3 lag x RS x %without vehicle	-0.001	-1.170	-0.001	-0.590	0.002	2.122	0.002	2.335	0.000	0.239	-0.001	-1.000
		HW 3 lag x RS x %living in group quarters	0.000	0.368	0.001	1.489	-0.001	-1.430	-0.002	-2.210	0.000	0.468	0.000	-0.270

		Dependent Variables											
			Medical Admissions		ED Visits		Urgent Care Visits		Observational Stays Without ED		PCP Visits		Specialist Visits	
		Effect (Explanatory Variables)	Estimate	Estimate x 1,000	Estimate	Estimate x 1,000	Estimate	Estimate x 1,000	Estimate	Estimate x 1,000	Estimate	Estimate x 1,000	Estimate	Estimate x 1,000
	Direct Effect	**Current month ozone moderate or worse (OZ 0 lag)**	0.000	0.022	0.000	0.073	0.000	-0.120	0.000	-0.020	0.000	0.009	0.000	-0.020
Current month's Ozone Hazard	Interaction Effect	OZ 0 lag x RS x %unemployment	-0.028	-28.010	-0.017	-17.390	-0.071	-70.700	0.064	63.830	-0.028	-27.720	0.029	29.450
		OZ 0 lag x RS x %w limited English language capabilities	0.003	3.414	0.007	6.751	-0.004	-3.930	-0.002	-1.880	0.003	3.092	-0.008	-7.760
		OZ 0 lag x RS x %identified as nonwhite	0.002	1.649	0.000	-0.090	0.005	5.170	-0.005	-4.830	0.001	1.063	-0.002	-1.860
		OZ 0 lag x RS x %uninsured	-0.001	-0.960	0.006	6.011	-0.006	-5.560	-0.005	-4.730	-0.004	-4.380	-0.001	-0.790
		OZ 0 lag x RS x %living in mobile homes	0.007	7.271	0.032	31.840	0.003	2.692	-0.021	-20.690	-0.005	-5.200	-0.004	-3.580
		OZ 0 lag x RS x %living in crowded housing units	-0.030	-30.230	-0.033	-32.770	-0.032	-31.870	0.100	100.000	0.009	9.366	0.045	45.180
		OZ 0 lag x RS x %without vehicle	0.013	13.050	0.013	12.530	0.023	23.070	-0.062	-61.660	-0.025	-25.010	0.000	-0.020
		OZ 0 lag x RS x %living in group quarters	0.007	6.919	-0.008	-7.990	0.021	20.500	0.008	7.502	0.031	31.440	-0.014	-14.160
	Direct Effect	**OZ days 1 month ago (OZ 1 Lag)**	0.000	-0.030	0.000	0.013	0.000	0.006	0.000	0.013	0.000	0.094	0.000	-0.030
Previous month's Ozone Hazard	Lagged Effect, 1-Month La	OZ 1 lag x RS x %unemployment	0.011	10.530	0.000	0.412	0.014	14.140	-0.086	-86.210	-0.009	-9.120	-0.019	-19.280
		OZ 1 lag x RS x %w limited English language capabilities	-0.002	-2.320	0.005	5.114	0.004	4.363	0.022	22.080	0.012	11.910	0.003	2.649
		OZ 1 lag x RS x %identified as nonwhite	0.000	-0.480	0.001	0.568	0.000	-0.360	0.002	2.413	-0.003	-2.670	0.002	1.781
		OZ 1 lag x RS x %uninsured	0.000	0.060	0.004	3.883	0.001	0.997	0.018	18.330	0.004	4.204	-0.001	-1.180
		OZ 1 lag x RS x %living in mobile homes	-0.006	-6.420	-0.002	-1.850	-0.009	-8.890	0.095	95.230	0.040	39.640	-0.007	-7.370
		OZ 1 lag x RS x %living in crowded housing units	0.016	16.200	-0.030	-29.670	-0.007	-6.510	-0.136	-135.600	-0.015	-15.420	-0.027	-27.470
		OZ 1 lag x RS x %without vehicle	-0.007	-7.410	-0.011	-11.340	-0.022	-22.110	0.056	56.320	0.020	20.150	0.002	1.684
		OZ 1 lag x RS x %living in group quarters	-0.003	-2.550	-0.001	-1.110	0.003	2.555	-0.020	-20.140	0.004	4.104	0.011	10.870
	Direct Effect	**OZ days 2 months ago (OZ 2 Lag)**	0.000	0.064	0.000	0.022	0.000	0.012	0.000	0.040	0.000	-0.080	0.000	0.001
Previous 2 months Ozone Hazard	Lagged Effect, 1-Month La	OZ 2 lag x RS x %unemployment	-0.024	-24.160	-0.029	-28.500	-0.021	-21.010	0.017	16.990	-0.002	-1.550	0.006	6.428
		OZ 2 lag x RS x %w limited English language capabilities	-0.005	-4.710	-0.001	-0.670	0.000	0.263	-0.005	-5.480	0.012	12.120	-0.009	-9.210
		OZ 2 lag x RS x %identified as nonwhite	0.002	2.102	0.000	0.379	0.000	-0.320	-0.001	-0.880	0.000	0.485	-0.001	-1.290
		OZ 2 lag x RS x %uninsured	-0.005	-4.950	-0.004	-3.580	-0.001	-0.800	0.003	2.679	0.008	7.678	-0.004	-3.810
		OZ 2 lag x RS x %living in mobile homes	-0.016	-16.330	0.011	11.210	0.019	19.380	-0.004	-4.120	0.011	10.770	0.003	2.841
		OZ 2 lag x RS x %living in crowded housing units	-0.004	-3.530	0.005	4.531	0.003	3.110	0.035	35.450	-0.055	-55.400	0.052	52.180
		OZ 2 lag x RS x %without vehicle	0.009	8.773	0.023	22.990	0.025	25.370	-0.024	-24.320	-0.018	-18.430	0.013	13.200
		OZ 2 lag x RS x %living in group quarters	0.016	16.420	0.013	13.490	0.003	2.747	-0.010	-10.150	0.001	0.737	-0.004	-4.490
	Direct Effect	**OZ days 3 months ago (OZ 3 Lag)**	0.000	-0.005	0.000	0.094	0.000	-0.120	0.000	-0.050	0.000	0.034	0.000	0.084
Previous 3 months Ozone Hazard	Lagged Effect, 1-Month La	OZ 3 lag x RS x %unemployment	-0.011	-11.150	-0.021	-21.220	-0.045	-45.490	-0.068	-68.220	0.014	14.160	-0.025	-25.310
		OZ 3 lag x RS x %w limited English language capabilities	0.003	2.749	-0.005	-4.850	0.007	6.961	-0.004	-3.830	-0.010	-10.320	-0.007	-7.040
		OZ 3 lag x RS x %identified as nonwhite	0.002	1.751	0.003	3.148	0.006	5.854	0.007	7.170	-0.001	-0.850	0.005	4.749
		OZ 3 lag x RS x %uninsured	-0.001	-0.660	-0.004	-4.460	-0.001	-0.680	-0.012	-11.510	-0.005	-4.840	-0.006	-5.710
		OZ 3 lag x RS x %living in mobile homes	-0.011	-10.620	-0.027	-27.230	-0.032	-32.330	-0.051	-50.950	-0.017	-16.730	-0.046	-46.210
		OZ 3 lag x RS x %living in crowded housing units	-0.029	-29.290	-0.018	-18.320	-0.086	-85.890	-0.035	-34.720	0.057	57.200	-0.027	-27.070
		OZ 3 lag x RS x %without vehicle	-0.007	-6.670	-0.002	-2.410	-0.016	-15.520	-0.016	-16.480	-0.009	-8.740	-0.012	-11.740
		OZ 3 lag x RS x %living in group quarters	0.008	7.905	0.015	15.130	0.025	24.980	0.046	45.760	0.005	5.027	0.020	19.610

			Dependent Variables											
			Medical Admissions		ED Visits		Urgent Care Visits		Observational Stays Without ED		PCP Visits		Specialist Visits	
		Effect (Explanatory Variables)	Estimate	Estimate x 1,000	Estimate	Estimate x 1,000	Estimate	Estimate x 1,000	Estimate	Estimate x 1,000	Estimate	Estimate x 1,000	Estimate	Estimate x 1,000
Current month's PM2.5 Hazard	Direct Effect	Current month PM2.5 moderate or worse (PM2.5 0 lag)	0.000	-0.090	0.000	-0.040	0.000	-0.040	0.000	-0.060	0.000	0.045	0.000	-0.060
	Interaction Effect	PM2.5 0 lag x RS x %unemployment	0.001	1.248	-0.006	-5.730	0.011	10.630	-0.023	-22.830	-0.016	-16.150	0.000	0.032
		PM2.5 0 lag x RS x %w limited English language capabilities	-0.005	-4.680	0.006	6.090	-0.016	-15.540	0.014	13.840	0.022	22.060	-0.006	-6.400
		PM2.5 0 lag x RS x %identified as nonwhite	0.000	0.049	0.001	0.700	0.000	0.239	0.001	0.851	-0.001	-0.720	0.001	0.750
		PM2.5 0 lag x RS x %uninsured	-0.002	-1.910	0.006	5.752	-0.001	-1.030	0.006	6.234	0.010	9.672	-0.003	-3.290
		PM2.5 0 lag x RS x %living in mobile homes	-0.001	-1.070	0.013	13.260	-0.009	-8.690	0.026	25.780	0.038	37.890	-0.010	-9.790
		PM2.5 0 lag x RS x %living in crowded housing units	0.020	19.810	-0.037	-37.400	0.052	51.830	-0.061	-60.860	-0.079	-79.270	0.019	18.590
		PM2.5 0 lag x RS x %without vehicle	0.003	3.196	-0.003	-3.300	-0.003	-3.020	0.000	-0.290	0.000	0.141	0.000	0.407
		PM2.5 0 lag x RS x %living in group quarters	-0.001	-1.480	-0.010	-9.580	-0.014	-14.040	0.000	0.010	0.002	2.067	0.000	0.165
Previous month's PM2.5 Hazard	Direct Effect	PM2.5 days 1 month ago (PM2.5 1 Lag)	0.000	-0.008	0.000	-0.004	0.000	0.003	0.000	-0.050	0.000	-0.090	0.000	0.009
	Interaction Effect	PM2.5 1 lag x RS x %unemployment	0.004	3.743	-0.002	-1.610	0.016	15.910	0.015	15.040	0.000	-0.220	0.005	5.431
		PM2.5 1 lag x RS x %w limited English language capabilities	-0.011	-10.770	0.003	2.928	-0.015	-15.010	0.009	8.808	0.010	9.757	-0.009	-9.210
		PM2.5 1 lag x RS x %identified as nonwhite	0.001	0.965	0.000	0.186	-0.002	-1.650	-0.001	-1.370	0.001	0.555	0.000	-0.050
		PM2.5 1 lag x RS x %uninsured	-0.003	-2.820	0.001	0.842	-0.004	-4.390	-0.001	-1.050	0.002	2.426	-0.003	-2.680
		PM2.5 1 lag x RS x %living in mobile homes	-0.019	-19.480	-0.002	-1.900	-0.008	-8.000	-0.006	-6.240	-0.002	-2.190	-0.011	-10.840
		PM2.5 1 lag x RS x %living in crowded housing units	0.029	28.830	-0.014	-13.630	0.074	73.880	-0.016	-16.420	-0.047	-47.360	0.036	36.230
		PM2.5 1 lag x RS x %without vehicle	-0.005	-4.920	-0.002	-2.210	0.011	10.650	0.001	0.622	-0.003	-2.890	0.000	-0.410
		PM2.5 1 lag x RS x %living in group quarters	-0.001	-0.730	0.003	3.075	-0.002	-2.370	0.009	8.608	0.004	3.606	-0.001	-0.560
Previous 2 months' PM2.5 Hazard	Direct Effect	PM2.5 days 2 months ago (PM2.5 2 Lag)	0.000	-0.050	0.000	-0.020	0.000	-0.030	0.000	-0.070	0.000	0.036	0.000	-0.020
	Interaction Effect	PM2.5 2 lag x RS x %unemployment	0.004	4.346	0.001	0.806	0.000	-0.320	-0.013	-13.150	-0.009	-9.010	0.000	0.059
		PM2.5 2 lag x RS x %w limited English language capabilities	0.002	1.989	0.001	1.029	-0.005	-4.530	0.004	3.697	0.004	3.569	0.001	0.707
		PM2.5 2 lag x RS x %identified as nonwhite	-0.001	-1.050	0.000	-0.030	0.001	0.938	0.001	0.682	-0.001	-0.680	0.000	0.129
		PM2.5 2 lag x RS x %uninsured	-0.001	-0.860	0.003	2.729	0.000	-0.110	0.003	2.738	-0.001	-1.350	0.000	0.089
		PM2.5 2 lag x RS x %living in mobile homes	0.007	6.948	0.008	8.307	-0.007	-7.000	0.010	9.968	0.004	4.364	0.000	-0.020
		PM2.5 2 lag x RS x %living in crowded housing units	0.008	7.605	-0.007	-7.280	0.006	5.682	-0.019	-19.130	0.004	3.790	-0.005	-4.870
		PM2.5 2 lag x RS x %without vehicle	0.005	5.378	-0.001	-0.700	-0.006	-5.650	0.000	-0.200	0.004	3.942	0.001	0.625
		PM2.5 2 lag x RS x %living in group quarters	0.001	1.395	-0.007	-7.420	-0.003	-3.460	-0.002	-1.750	0.011	11.020	0.000	-0.008
Previous 3 months' PM2.5 Hazard	Direct Effect	PM2.5 days 3 months ago (PM2.5 3 Lag)	0.000	-0.002	0.000	-0.030	0.000	0.036	0.000	0.037	0.000	0.041	0.000	-0.020
	Interaction Effect	PM2.5 3 lag x RS x %unemployment	0.012	11.570	0.009	9.085	0.007	7.312	-0.003	-3.170	-0.015	-15.100	0.014	14.230
		PM2.5 3 lag x RS x %w limited English language capabilities	0.003	2.975	0.004	3.529	-0.002	-2.280	0.004	3.719	0.011	10.540	-0.001	-0.860
		PM2.5 3 lag x RS x %identified as nonwhite	-0.002	-2.320	-0.001	-1.370	0.000	-0.390	-0.001	-0.780	-0.001	-1.250	-0.001	-1.470
		PM2.5 3 lag x RS x %uninsured	-0.002	-1.970	0.003	3.270	-0.001	-0.890	0.002	1.820	0.002	2.128	-0.003	-2.920
		PM2.5 3 lag x RS x %living in mobile homes	0.006	5.641	0.015	14.510	0.007	6.523	0.015	14.990	0.026	25.580	-0.004	-4.090
		PM2.5 3 lag x RS x %living in crowded housing units	0.018	18.070	-0.002	-1.590	0.010	9.870	-0.003	-3.220	-0.017	-16.860	0.022	21.820
		PM2.5 3 lag x RS x %without vehicle	0.011	10.980	0.004	3.565	0.003	2.956	0.000	-0.330	0.006	6.186	0.006	5.529
		PM2.5 3 lag x RS x %living in group quarters	0.006	6.228	-0.009	-9.330	-0.008	-7.720	0.000	-0.210	0.008	8.125	0.003	2.605
Current month's PM10 Hazard	Direct Effect	Current month PM10 moderate or worse (PM10 0 lag)	0.000	0.026	0.000	-0.090	0.000	0.092	0.000	-0.240	0.000	-0.170	0.000	-0.060
	Interaction Effect	PM10 0 lag x RS x %unemployment	-0.010	-9.670	-0.013	-13.310	0.018	17.610	0.010	10.100	-0.002	-1.830	-0.018	-17.600
		PM10 0 lag x RS x %w limited English language capabilities	-0.018	-18.230	-0.008	-8.000	-0.026	-26.410	0.000	0.423	-0.036	-36.150	0.014	14.460
		PM10 0 lag x RS x %identified as nonwhite	0.003	2.926	0.002	1.879	-0.001	-1.260	0.000	0.332	0.003	3.185	0.001	0.822
		PM10 0 lag x RS x %uninsured	-0.005	-5.150	-0.004	-4.110	-0.008	-8.130	0.005	4.689	-0.014	-13.610	0.005	5.301
		PM10 0 lag x RS x %living in mobile homes	-0.033	-33.410	-0.016	-16.320	-0.024	-24.160	0.000	-0.310	-0.041	-41.310	0.014	14.390
		PM10 0 lag x RS x %living in crowded housing units	0.039	38.500	0.017	17.070	0.115	115.400	-0.015	-14.650	0.118	117.800	-0.065	-64.800
		PM10 0 lag x RS x %without vehicle	-0.012	-12.300	-0.005	-5.360	0.004	4.331	-0.002	-1.940	0.003	2.969	-0.006	-5.620
		PM10 0 lag x RS x %living in group quarters	0.005	4.834	0.011	10.760	0.004	4.149	-0.011	-11.290	-0.027	-27.280	0.013	12.520
Previous month's PM10 Hazard	Direct Effect	PM10 days 1 month ago (PM10 1 Lag)	0.000	-0.190	0.000	0.041	0.000	-0.110	0.000	0.118	0.000	0.167	0.000	-0.040
	Interaction Effect	PM10 1 lag x RS x %unemployment	-0.019	-19.120	-0.021	-21.010	-0.013	-13.160	-0.009	-8.750	-0.014	-14.480	-0.025	-25.260
		PM10 1 lag x RS x %w limited English language capabilities	0.010	10.080	-0.001	-0.880	-0.015	-15.270	-0.006	-6.260	-0.018	-17.720	0.021	20.720
		PM10 1 lag x RS x %identified as nonwhite	0.001	1.437	0.002	2.202	0.002	2.045	0.000	-0.410	-0.001	-0.670	0.003	3.486
		PM10 1 lag x RS x %uninsured	0.002	2.265	0.000	0.110	-0.003	-2.640	-0.001	-1.350	-0.010	-9.780	0.007	7.499
		PM10 1 lag x RS x %living in mobile homes	0.014	13.650	0.003	3.441	0.002	2.314	0.023	23.170	0.005	4.819	0.004	3.897
		PM10 1 lag x RS x %living in crowded housing units	-0.046	-46.270	-0.015	-15.230	0.040	39.820	0.032	31.740	0.098	97.540	-0.121	-120.900
		PM10 1 lag x RS x %without vehicle	-0.002	-2.340	-0.005	-5.290	-0.002	-1.720	0.002	2.437	0.011	10.590	-0.016	-16.280
		PM10 1 lag x RS x %living in group quarters	0.002	1.734	-0.005	-5.490	-0.011	-11.200	-0.001	-1.420	0.002	1.668	0.001	0.596
Previous 2 months' PM10 Hazard	Direct Effect	PM10 days 2 months ago (PM10 2 Lag)	0.000	-0.060	0.000	-0.030	0.000	-0.170	0.000	0.005	0.000	0.123	0.000	-0.020
	Interaction Effect	PM10 2 lag x RS x %unemployment	0.001	1.027	0.010	10.440	-0.011	-10.730	-0.012	-12.400	-0.004	-4.420	0.004	4.475
		PM10 2 lag x RS x %w limited English language capabilities	0.003	3.085	0.000	-0.290	-0.008	-7.580	-0.022	-21.620	-0.020	-20.440	0.008	7.972
		PM10 2 lag x RS x %identified as nonwhite	-0.001	-0.860	-0.002	-1.660	0.001	0.528	0.000	0.322	0.001	1.115	-0.002	-2.170
		PM10 2 lag x RS x %uninsured	0.004	4.333	0.002	2.126	-0.002	-2.060	-0.015	-14.910	-0.009	-9.070	0.004	3.740
		PM10 2 lag x RS x %living in mobile homes	0.024	23.750	0.020	19.730	0.011	11.420	-0.017	-16.710	-0.013	-13.270	0.025	25.080
		PM10 2 lag x RS x %living in crowded housing units	-0.005	-5.490	0.020	19.550	0.034	34.160	0.103	102.700	0.080	80.170	-0.008	-7.620
		PM10 2 lag x RS x %without vehicle	0.005	4.902	0.006	5.846	0.002	2.436	0.016	15.560	0.004	3.782	0.006	6.130
		PM10 2 lag x RS x %living in group quarters	-0.014	-14.180	-0.017	-16.720	-0.004	-3.500	0.008	7.870	-0.022	-22.310	0.002	2.073
Previous 3 months' PM10 Hazard	Direct Effect	PM10 days 3 months ago (PM10 3 Lag)	0.000	0.094	0.000	0.134	0.000	-0.160	0.000	-0.080	0.000	0.005	0.000	-0.060
	Interaction Effect	PM10 3 lag x RS x %unemployment	0.010	10.130	0.021	20.860	0.001	1.069	0.006	6.482	-0.009	-8.800	0.016	16.240
		PM10 3 lag x RS x %w limited English language capabilities	0.002	2.313	0.004	3.781	0.001	0.505	-0.007	-6.800	-0.015	-14.990	0.007	6.670
		PM10 3 lag x RS x %identified as nonwhite	-0.003	-2.640	-0.004	-4.430	-0.001	-0.870	-0.001	-1.440	0.002	1.985	-0.004	-4.110
		PM10 3 lag x RS x %uninsured	0.006	5.695	0.001	1.048	0.001	0.988	0.001	1.055	-0.007	-6.930	0.005	5.137
		PM10 3 lag x RS x %living in mobile homes	0.034	34.300	0.029	28.820	0.020	20.020	0.009	8.676	-0.005	-4.910	0.041	40.580
		PM10 3 lag x RS x %living in crowded housing units	0.018	17.700	0.036	35.810	0.014	13.540	0.045	44.790	0.051	50.700	0.019	19.070
		PM10 3 lag x RS x %without vehicle	0.007	7.416	0.017	17.130	0.007	6.793	0.007	6.611	0.002	1.693	0.018	17.690
		PM10 3 lag x RS x %living in group quarters	-0.023	-22.930	-0.010	-10.000	-0.009	-9.440	-0.007	-7.210	-0.029	-29.430	-0.015	-14.830

Figure 3 includes the relative ranking of the explanatory variables and the direction of their impact on utilization within a model. Cells highlighted in red are the top explanatory variables, ranked by the percent of contribution toward error reduction. Please note that this figure only includes the variables relating to extreme heat and air pollutants and their interactions with other nonclimate variables, from the current month and from prior months (lag variables). A positive sign means that the coefficient is positive, which means that when everything else is held constant, an increase in the explanatory variable is associated with an increase in the utilization count. A negative sign, on the other hand, means that when everything else is held constant, an increase in the explanatory variable is associated with a decrease in the utilization count. The visual helps us understand the different temporal dynamics of climate events' association with healthcare utilization.

The effects of air pollutants on healthcare utilization are observed to take effect more immediately. This immediate impact could be attributed to the direct and acute nature of respiratory symptoms triggered by air pollution. Inhaling pollutants can quickly exacerbate conditions like asthma, bronchitis, and other respiratory issues, leading to an urgent need for healthcare services. This immediacy in response underscores the critical nature of air quality as a public health concern, necessitating prompt and effective mitigation measures to protect vulnerable populations.

In contrast, the impact of extreme heat on healthcare utilization is more delayed, becoming significantly noticeable after a period of two to three months. This delay may be attributed to worsening chronic conditions such as heart failure exacerbated by extreme heat. For example, prolonged exposure to high temperatures can lead to dehydration, electrolyte imbalances, and stress on the cardiovascular system, which may culminate in more serious health issues over time. Similarly, heat stroke, a life-threatening condition may develop after continued exposure to extreme temperatures causing neurologic symptoms such as confusion, seizures and/or difficulty speaking.

Understanding these temporal patterns is valuable for climate preparedness planning and response. The immediate impact of air pollutants necessitates swift action to reduce exposure and provide medical care, especially during periods of high pollution. Public health advisories, air quality monitoring, and timely healthcare services are essential in these scenarios. The delayed effects of extreme heat, on the other hand, call for a more prolonged and sustained approach to climate preparedness, such as education on heat-related illness prevention, availability of cooling centers, and ongoing monitoring and support for individuals with chronic health conditions who might be more susceptible to the effects of prolonged heat exposure.

FIGURE 3: GENERALIZED LINEAR MODELS, PREDICTING HEALTHCARE UTILIZATION COUNTS RANKING AND DIRECTION OF COEFFICIENTS

			Dependent Variables											
			Medical Admissions		ED Visits		Urgent Care Visits		Observational Stays wo ED		PCP Visits		Specialist Visits	
		Effect	Rank	Sign	Rank	Sign	Rank	Sign	Rank	Sign	Rank	Sign	Rank	Sign
	Direct Effect	**Current HW days (HW 0 Lag)**	166	+	166	+	144	+	137	+	158	-	142	+
Current month's heatwave	Interaction effect	HW 0 lag x RS x %unemployment	114	-	72	-	23	+	88	+	67	+	34	-
		HW 0 lag x RS x %w limited English language capabilities	65	+	26	-	84	-	70	+	44	-	87	+
		HW 0 lag x RS x %identified as nonwhite	20	+	3	+	12	-	67	+	142	+	2	+
		HW 0 lag x RS x %uninsured	118	+	45	-	105	+	167	-	93	-	127	-
		HW 0 lag x RS x %living in mobile homes	91	-	32	-	111	+	101	-	97	-	43	-
		HW 0 lag x RS x %living in crowded housing units	25	-	112	-	21	+	33	-	49	+	9	-
		HW 0 lag x RS x %without vehicle	59	-	69	-	118	+	105	+	128	+	47	-
		HW 0 lag x RS x %living in group quarters	119	+	67	+	80	-	152	-	153	-	83	+
	Direct Effect	**Heatwave days 1 month ago (HW 1 Lag)**	149	+	159	+	147	+	132	+	149	-	133	+
Previous month's heatwave	Interaction effect	HW 1 lag x RS x %unemployment	101	-	102	-	41	+	26	+	33	+	94	-
		HW 1 lag x RS x %w limited English language capabilities	55	+	48	-	31	+	20	-	17	-	68	+
		HW 1 lag x RS x %identified as nonwhite	23	-	99	-	33	-	49	+	81	+	41	-
		HW 1 lag x RS x %uninsured	111	+	78	-	64	+	19	-	96	-	92	+
		HW 1 lag x RS x %living in mobile homes	61	+	129	-	123	+	24	-	62	-	76	+
		HW 1 lag x RS x %living in crowded housing units	144	+	21	+	26	-	22	+	30	+	152	-
		HW 1 lag x RS x %without vehicle	73	+	100	+	114	+	82	-	107	-	120	+
		HW 1 lag x RS x %living in group quarters	146	-	101	+	89	-	56	+	114	-	124	-
	Direct Effect	**Heatwave days 2 months ago (HW 2 Lag)**	155	+	168	-	165	+	133	+	156	-	146	+
Previous 2 months' heatwave	Interaction effect	HW 2 lag x RS x %unemployment	50	+	51	+	100	+	108	-	64	+	109	+
		HW 2 lag x RS x %w limited English language capabilities	19	+	53	-	15	+	44	-	60	-	121	+
		HW 2 lag x RS x %identified as nonwhite	22	-	58	-	59	+	38	+	105	+	91	+
		HW 2 lag x RS x %uninsured	49	+	116	+	54	+	84	-	160	-	101	+
		HW 2 lag x RS x %living in mobile homes	79	+	164	-	152	-	76	-	102	-	163	-
		HW 2 lag x RS x %living in crowded housing units	24	-	33	+	10	-	90	+	95	+	82	-
		HW 2 lag x RS x %without vehicle	133	-	110	-	73	-	129	+	121	-	90	-
		HW 2 lag x RS x %living in group quarters	88	-	96	-	126	-	123	+	120	-	110	-
	Direct Effect	**Heatwave days 3 months ago (HW 3 Lag)**	163	+	148	-	163	+	139	+	155	-	160	-
Previous 3 months' heatwave	Interaction effect	HW 3 lag x RS x %unemployment	70	-	88	-	24	+	14	+	85	+	46	-
		HW 3 lag x RS x %w limited English language capabilities	57	-	27	-	154	-	63	-	55	-	70	-
		HW 3 lag x RS x %identified as nonwhite	12	+	18	+	9	-	7	-	59	+	24	+
		HW 3 lag x RS x %uninsured	127	-	57	-	146	-	87	-	83	-	115	+
		HW 3 lag x RS x %living in mobile homes	92	-	73	-	75	+	126	+	78	-	122	-
		HW 3 lag x RS x %living in crowded housing units	78	-	37	+	16	+	13	+	104	+	71	-
		HW 3 lag x RS x %without vehicle	93	-	113	-	65	+	74	+	141	+	89	-
		HW 3 lag x RS x %living in group quarters	139	+	89	+	95	-	86	-	132	+	130	-
	Direct Effect	**Current month ozone moderate or worse (OZ 0 lag)**	156	+	119	+	108	-	146	-	157	+	148	-
Current month's Ozone Hazard	Interaction Effect	OZ 0 lag x RS x %unemployment	10	-	16	-	7	-	10	+	22	-	14	+
		OZ 0 lag x RS x %w limited English language capabilities	46	+	15	+	53	-	89	-	71	+	27	-
		OZ 0 lag x RS x %identified as nonwhite	7	+	117	-	3	+	4	-	39	+	10	-
		OZ 0 lag x RS x %uninsured	120	-	38	+	57	-	72	-	75	-	119	-
		OZ 0 lag x RS x %living in mobile homes	86	+	14	+	119	+	59	-	113	-	105	-
		OZ 0 lag x RS x %living in crowded housing units	13	-	8	-	20	-	6	+	77	+	8	+
		OZ 0 lag x RS x %without vehicle	52	+	60	+	40	+	18	-	46	-	167	-
		OZ 0 lag x RS x %living in group quarters	90	+	85	-	48	+	98	+	40	+	49	-
	Direct Effect	**OZ days 1 month ago (OZ 1 Lag)**	154	-	160	+	166	+	156	+	122	+	132	-
Previous month's Ozone Hazard	Lagged Effect, 1-Month La	OZ 1 lag x RS x %unemployment	38	+	152	+	42	+	5	-	66	-	30	-
		OZ 1 lag x RS x %w limited English language capabilities	64	-	24	+	46	+	11	+	16	+	56	+
		OZ 1 lag x RS x %identified as nonwhite	47	-	40	+	71	-	15	+	6	-	11	+
		OZ 1 lag x RS x %uninsured	167	+	68	+	117	+	25	+	79	+	106	-
		OZ 1 lag x RS x %living in mobile homes	98	-	130	-	83	-	12	+	28	+	79	-
		OZ 1 lag x RS x %living in crowded housing units	30	+	9	-	82	-	2	-	57	-	23	-
		OZ 1 lag x RS x %without vehicle	83	-	65	-	44	-	21	+	58	+	123	+
		OZ 1 lag x RS x %living in group quarters	123	-	143	-	122	+	60	-	119	+	64	+
	Direct Effect	**OZ days 2 months ago (OZ 2 Lag)**	128	+	149	+	164	+	135	+	124	-	165	+
Previous 2 months Ozone Hazard	Lagged Effect, 1-Month La	OZ 2 lag x RS x %unemployment	14	-	7	-	28	-	52	+	129	-	63	+
		OZ 2 lag x RS x %w limited English language capabilities	31	-	115	-	150	+	54	-	15	+	18	-
		OZ 2 lag x RS x %identified as nonwhite	4	+	66	+	77	-	53	-	68	+	21	-
		OZ 2 lag x RS x %uninsured	48	-	71	-	125	-	92	+	53	+	62	-
		OZ 2 lag x RS x %living in mobile homes	43	-	70	+	49	+	113	-	86	+	113	+
		OZ 2 lag x RS x %living in crowded housing units	109	-	94	+	106	+	29	+	9	-	5	+
		OZ 2 lag x RS x %without vehicle	76	+	25	+	34	+	55	-	61	-	50	+
		OZ 2 lag x RS x %living in group quarters	45	+	59	+	120	+	85	-	148	+	100	-
	Direct Effect	**OZ days 3 months ago (OZ 3 Lag)**	165	-	114	+	107	-	131	-	144	+	112	+
Previous 3 months Ozone Hazard	Lagged Effect, 1-Month La	OZ 3 lag x RS x %unemployment	35	-	10	-	13	-	9	-	52	+	19	-
		OZ 3 lag x RS x %w limited English language capabilities	58	+	28	-	29	+	62	-	20	-	31	-
		OZ 3 lag x RS x %identified as nonwhite	5	+	1	+	2	+	1	+	48	-	1	+
		OZ 3 lag x RS x %uninsured	134	-	61	-	130	-	42	-	72	-	40	-
		OZ 3 lag x RS x %living in mobile homes	69	-	19	-	30	-	28	-	65	-	16	-
		OZ 3 lag x RS x %living in crowded housing units	15	-	22	-	8	-	30	-	8	+	26	-
		OZ 3 lag x RS x %without vehicle	89	-	121	-	58	-	64	-	94	-	57	-
		OZ 3 lag x RS x %living in group quarters	84	+	49	+	39	+	32	+	116	+	36	+

			Dependent Variables											
			Medical Admissions		ED Visits		Urgent Care Visits		Observational Stays wo ED		PCP Visits		Specialist Visits	
		Effect	Rank	Sign	Rank	Sign	Rank	Sign	Rank	Sign	Rank	Sign	Rank	Sign
	Direct Effect	Current month PM2.5 moderate or worse (PM2.5 0 lag)	104	-	124	-	124	-	118	-	127	+	104	-
Current month's PM2.5 Hazard	Interaction Effect	PM2.5 0 lag x RS x %unemployment	116	+	55	-	36	+	23	-	27	-	162	+
		PM2.5 0 lag x RS x %w limited English language capabilities	16	-	5	+	4	-	8	+	2	+	12	-
		PM2.5 0 lag x RS x %identified as nonwhite	124	+	11	+	66	+	34	+	34	-	25	+
		PM2.5 0 lag x RS x %uninsured	62	-	12	+	96	-	40	+	13	+	35	-
		PM2.5 0 lag x RS x %living in mobile homes	142	-	43	+	70	-	45	+	19	+	55	-
		PM2.5 0 lag x RS x %living in crowded housing units	8	+	2	-	5	+	3	-	1	-	17	+
		PM2.5 0 lag x RS x %without vehicle	99	+	93	-	101	-	153	-	161	+	137	+
		PM2.5 0 lag x RS x %living in group quarters	132	-	62	-	50	-	168	+	125	+	156	+
	Direct Effect	PM2.5 days 1 month ago (PM2.5 1 Lag)	162	-	163	-	167	+	125	-	111	-	149	+
Previous month's PM2.5 Hazard	Interaction Effect	PM2.5 1 lag x RS x %unemployment	75	+	106	-	25	+	41	+	152	-	53	+
		PM2.5 1 lag x RS x %w limited English language capabilities	2	-	23	+	6	-	16	+	7	+	4	-
		PM2.5 1 lag x RS x %identified as nonwhite	9	+	80	+	11	-	17	-	45	+	118	-
		PM2.5 1 lag x RS x %uninsured	40	-	98	+	37	-	102	-	70	+	42	-
		PM2.5 1 lag x RS x %living in mobile homes	27	-	125	-	76	-	93	-	126	-	52	-
		PM2.5 1 lag x RS x %living in crowded housing units	3	+	13	-	1	+	36	-	3	-	3	+
		PM2.5 1 lag x RS x %without vehicle	74	-	103	-	47	+	138	+	110	-	139	-
		PM2.5 1 lag x RS x %living in group quarters	153	-	105	+	115	-	80	+	117	+	141	-
	Direct Effect	PM2.5 days 2 months ago (PM2.5 2 Lag)	117	-	139	-	135	-	111	-	131	+	126	-
Previous 2 months' PM2.5 Hazard	Interaction Effect	PM2.5 2 lag x RS x %unemployment	68	+	127	+	158	-	48	-	56	-	159	+
		PM2.5 2 lag x RS x %w limited English language capabilities	42	+	83	+	27	-	50	+	43	+	88	+
		PM2.5 2 lag x RS x %identified as nonwhite	6	-	135	-	19	+	43	+	37	-	84	+
		PM2.5 2 lag x RS x %uninsured	106	-	47	+	162	-	69	+	101	-	150	+
		PM2.5 2 lag x RS x %living in mobile homes	81	+	74	+	85	-	77	+	112	+	166	-
		PM2.5 2 lag x RS x %living in crowded housing units	36	+	39	-	62	+	31	-	92	+	59	-
		PM2.5 2 lag x RS x %without vehicle	71	+	138	-	72	-	159	-	103	+	131	+
		PM2.5 2 lag x RS x %living in group quarters	135	+	77	-	104	-	128	-	69	+	168	-
	Direct Effect	PM2.5 days 3 months ago (PM2.5 3 Lag)	168	-	131	-	128	+	130	+	130	+	128	-
Previous 3 months' PM2.5 Hazard	Interaction Effect	PM2.5 3 lag x RS x %unemployment	26	+	30	+	55	+	95	-	32	-	28	+
		PM2.5 3 lag x RS x %w limited English language capabilities	29	+	17	+	52	-	51	+	5	+	81	-
		PM2.5 3 lag x RS x %identified as nonwhite	1	-	4	-	51	-	39	-	11	-	6	-
		PM2.5 3 lag x RS x %uninsured	63	-	35	+	103	-	83	+	80	+	39	-
		PM2.5 3 lag x RS x %living in mobile homes	94	+	42	+	87	+	61	+	41	+	95	-
		PM2.5 3 lag x RS x %living in crowded housing units	11	+	111	-	43	+	94	-	25	-	13	+
		PM2.5 3 lag x RS x %without vehicle	32	+	91	+	102	+	150	-	84	+	67	+
		PM2.5 3 lag x RS x %living in group quarters	82	+	64	-	74	-	160	-	87	+	107	+
	Direct Effect	Current month PM10 moderate or worse (PM10 0 lag)	164	+	140	-	151	+	119	-	134	-	143	-
Current month's PM10 Hazard	Interaction Effect	PM10 0 lag x RS x %unemployment	97	-	81	-	67	+	100	+	143	-	58	-
		PM10 0 lag x RS x %w limited English language capabilities	18	-	52	-	18	-	147	+	10	-	32	+
		PM10 0 lag x RS x %identified as nonwhite	17	+	29	+	60	-	114	+	29	+	69	+
		PM10 0 lag x RS x %uninsured	108	-	109	-	86	-	109	+	76	-	93	+
		PM10 0 lag x RS x %living in mobile homes	66	-	97	-	88	-	164	-	73	-	97	+
		PM10 0 lag x RS x %living in crowded housing units	33	+	82	+	14	+	96	-	12	+	29	-
		PM10 0 lag x RS x %without vehicle	102	-	122	-	131	+	144	-	140	+	117	-
		PM10 0 lag x RS x %living in group quarters	136	+	108	+	143	+	112	-	89	-	99	+
	Direct Effect	PM10 days 1 month ago (PM10 1 Lag)	126	-	158	+	145	-	134	+	133	+	147	-
Previous month's PM10 Hazard	Interaction Effect	PM10 1 lag x RS x %unemployment	56	-	54	-	81	-	103	-	90	-	38	-
		PM10 1 lag x RS x %w limited English language capabilities	34	+	133	-	32	-	79	-	38	-	22	+
		PM10 1 lag x RS x %identified as nonwhite	39	+	20	+	38	+	107	-	100	-	20	+
		PM10 1 lag x RS x %uninsured	130	+	165	+	121	-	136	-	91	-	78	+
		PM10 1 lag x RS x %living in mobile homes	110	+	142	+	159	+	97	+	137	+	129	+
		PM10 1 lag x RS x %living in crowded housing units	28	-	84	-	45	+	66	+	18	+	7	-
		PM10 1 lag x RS x %without vehicle	152	-	123	-	157	-	140	+	115	+	77	-
		PM10 1 lag x RS x %living in group quarters	160	+	126	-	109	-	154	-	150	+	157	+
	Direct Effect	PM10 days 2 months ago (PM10 2 Lag)	157	-	161	-	129	-	166	+	138	+	155	-
Previous 2 months' PM10 Hazard	Interaction Effect	PM10 2 lag x RS x %unemployment	158	+	87	+	91	-	91	-	123	-	111	+
		PM10 2 lag x RS x %w limited English language capabilities	103	+	157	-	63	-	37	-	31	-	45	+
		PM10 2 lag x RS x %identified as nonwhite	72	-	34	-	97	+	115	+	74	+	33	-
		PM10 2 lag x RS x %uninsured	113	+	128	+	134	-	73	-	98	-	108	+
		PM10 2 lag x RS x %living in mobile homes	85	+	92	+	113	+	106	-	118	-	74	+
		PM10 2 lag x RS x %living in crowded housing units	121	-	76	+	56	+	27	+	24	+	103	-
		PM10 2 lag x RS x %without vehicle	129	+	118	+	153	+	99	+	135	+	114	+
		PM10 2 lag x RS x %living in group quarters	105	-	95	-	149	-	122	+	99	-	140	+
	Direct Effect	PM10 days 3 months ago (PM10 3 Lag)	150	+	134	+	136	-	142	-	167	+	145	-
Previous 3 months' PM10 Hazard	Interaction Effect	PM10 3 lag x RS x %unemployment	95	+	56	+	160	+	110	+	108	-	65	+
		PM10 3 lag x RS x %w limited English language capabilities	112	+	90	+	156	+	78	-	47	-	60	+
		PM10 3 lag x RS x %identified as nonwhite	21	-	6	-	79	-	68	-	54	+	15	-
		PM10 3 lag x RS x %uninsured	107	+	146	+	155	+	143	+	106	-	98	+
		PM10 3 lag x RS x %living in mobile homes	60	+	75	+	92	+	121	+	136	-	48	+
		PM10 3 lag x RS x %living in crowded housing units	80	+	41	+	94	+	57	+	50	+	72	+
		PM10 3 lag x RS x %without vehicle	115	+	86	+	116	+	120	+	146	+	75	+
		PM10 3 lag x RS x %living in group quarters	77	-	107	-	112	-	124	-	82	-	86	-

4.2 VISUALIZING THE VARIABLE IMPACTS ON SUBPOPULATIONS

The preceding section demonstrated the magnitude and statistical significance of climate events' variable impacts on healthcare utilization, highlighting differences by visit type, community, and social context. To further illustrate these patterns, Figures 4 and 5 provide a more intuitive perspective on how extreme heat and air pollution interact with social determinants of health to influence fluctuations in care demand.

Figure 4 below depicts the variability in healthcare utilization among populations in crowded housing exposed to extreme heat and poor air quality. Timing of impacts is shown using shades of blue, with lighter shades indicating immediate effects and darker shades representing delayed responses. The figure also differentiates facility-based visits (e.g., medical admissions, ED visits, observational stays) from professional visits (e.g., PCP, specialist, and urgent care visits), offering a clearer view of climate-driven utilization shifts.

Air pollution, particularly PM10, drives substantial fluctuations in utilization. For example, in high PM10 exposure areas, ED visits and observational stays decline initially but peak later, with observational stays reaching 102.7 per 1,000 after two months. In contrast, professional visits show greater increases in the immediate months, suggesting different care-seeking behaviors based on visit type and lagged health effects.

Compared to air pollution, extreme heat exhibits smaller variability across all visit types, suggesting more stable but still significant effects, particularly for dehydration and cardiovascular issues. The immediate and fluctuating impact of air pollution, particularly on respiratory conditions, reinforces the need for predictive models that integrate both social and environmental determinants of health to better anticipate climate-driven healthcare shifts.

FIGURE 4: VARIABILITY IN HEALTHCARE UTILIZATION IMPACT (RATES PER 1,000) AMONG POPULATIONS IN CROWDED HOUSING EXPOSED TO ENVIRONMENTAL STRESSORS

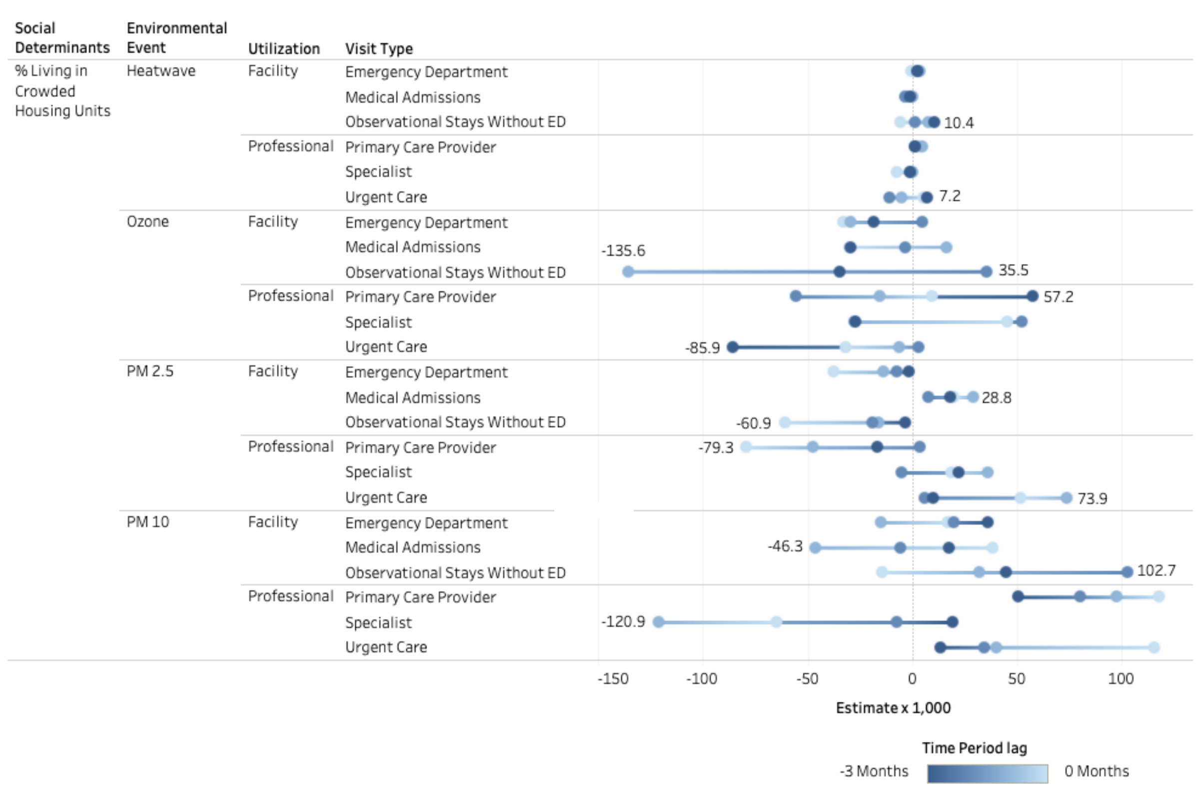
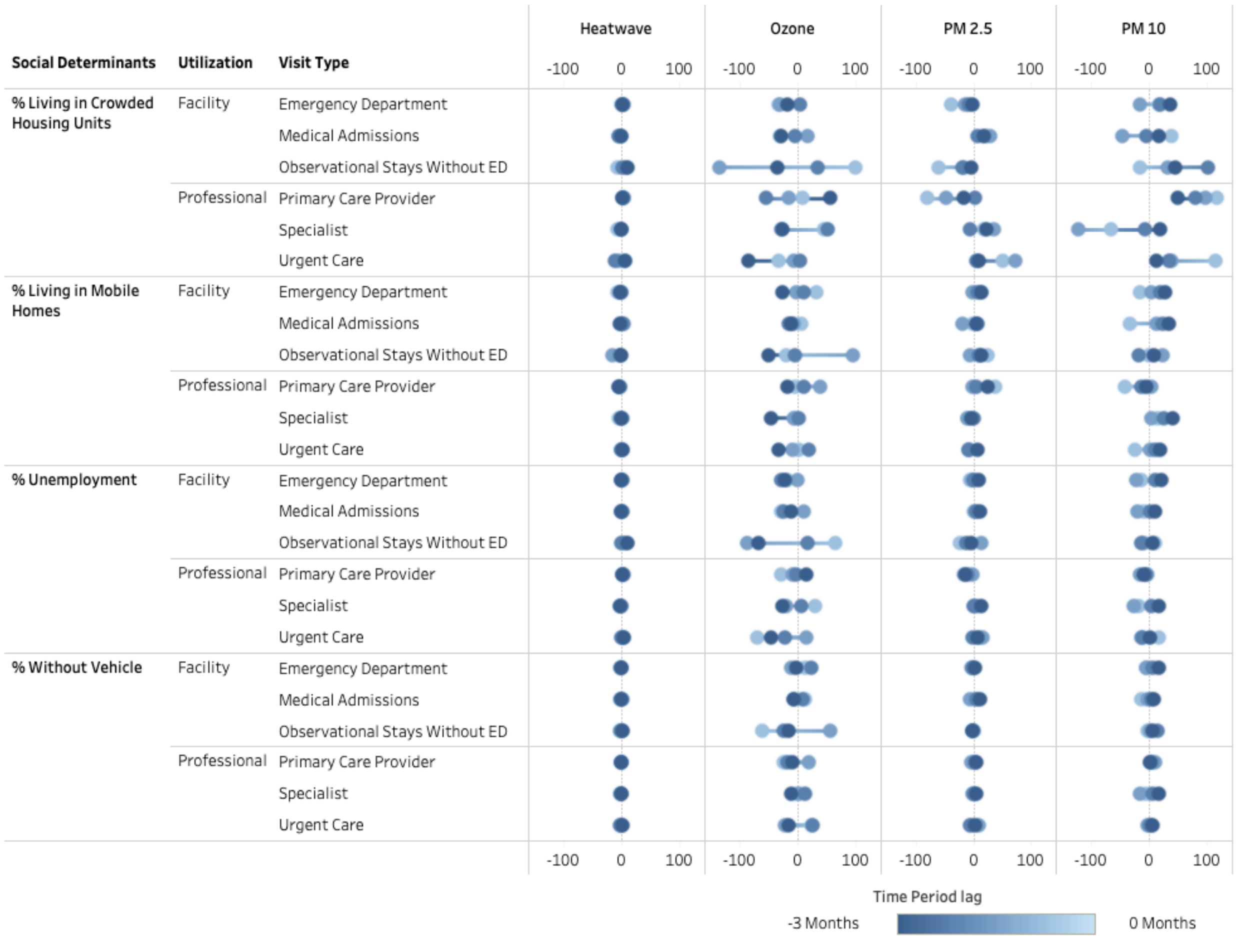


Figure 5 further explores how social needs, such as the percentage of the population living in crowded housing, modify healthcare utilization variability over time in response to air pollution and extreme heat. The visualization underscores that the interaction of social determinants and environmental stressors influences health outcomes in complex ways, with air pollution showing greater variability over longer time lags compared to extreme heat.

FIGURE 5: VARIABILITY IN HEALTHCARE UTILIZATION IMPACT (RATES PER 1,000) BY SOCIAL NEED AND TYPE OF ENVIRONMENTAL EVENT



5. Limitations

This section describes the limitations of our study.

5.1 DATA RELIANCE

In performing the analysis, we relied on data and other information obtained from the National Centers for Environmental Information (NCEI), the U.S. Census Bureau, the CDC, and other sources. Beyond the scope of work as previously described, we did not audit, verify, or review the data and other information for reasonableness and consistency. Such a review is beyond the scope of this assignment. If the underlying data or information is inaccurate or incomplete, the results of this analysis may likewise be inaccurate or incomplete. In that event, the results of this analysis may not be suitable for the intended purpose.

5.2 VARIABILITY OF RESULTS

This analysis and modeling are based on sound statistical principles, but it is important to note that variation from the model results is not only possible, but, in fact, probable. While the degree of such variation cannot be quantified, it could be in either direction from the results contained in this report. Such uncertainty is inherent in any set of statistical and actuarial modeling.

It is important to recognize that healthcare utilization is influenced by a multitude of factors. Some of these factors are observable or can be estimated with existing data, such as an individual's health status, socioeconomic status, insurance coverage, seasonality, and environmental conditions like extreme heat and poor air quality. However, there are also factors that remain unobservable for this analysis and for which we lack effective proxies to estimate. These include variables such as provider availability during extreme weather or pollution events (e.g., whether a medical practice is open and fully staffed), an individual’s profession (particularly whether they work indoors or outdoors), their work schedule (such as flexibility to adjust job duties to less extreme weather conditions), and their level of protection against heat and air pollution.

The presence of these unobserved factors could introduce biases in the estimations of this analysis and may lead to misinterpretations of the results. While the precise direction and magnitude of these potential biases are not well understood in the analysis, we advise readers to be aware of these limitations. Caution should be exercised in interpreting the study's findings, keeping in mind these unaccounted factors that could impact healthcare utilization.

6. Conclusion: An environmental call-to-action for the healthcare industry

While there is a growing foundation of research to quantify the impacts of climate events on health, less is known about the actual utilization trends—more research in this particular field is needed. As climate events and environmental determinants of health continue to intensify, there is an urgent need to:

- **Ensure resiliency for vulnerable populations in California,** particularly around extreme heat and poor air quality through increased education, outreach and tangible resources. Activations could include providing access to air-filtration machines and masks, supporting community clean-air centers that mimic community cooling centers, expanding outreach programs to check on vulnerable individuals, expanding education on particular risks of certain populations, increasing access to the AQI and other tools for monitoring air quality, and supporting policies that electrify our transportation fleet or aim to decrease industrial pollution.
- Engage with providers and other healthcare stakeholders to better understand the impacts of environment on utilization for two reasons:
  - **System resilience**. By understanding acute and chronic impacts of environmental events on healthcare utilization, the healthcare system can better meet health needs as the climate continues to change, preventing unnecessary health harms and unmet healthcare needs.
  - **Long-term affordability**. Healthcare is priced based on expected need for care, so variation, lack of predictability, and greater strain on the healthcare system could all influence the cost of care in the long run. With healthcare costs expected to continue rising, health plans must look ahead to understand what is influencing healthcare utilization needs and costs to better control them and achieve long-term affordability goals.[20]

To learn more about Blue Shield of California's commitment to protecting the health of the environment and California communities, visit citizenship.blueshieldca.com.

20. PricewaterhouseCoopers. (November 2024). Medical cost trend: Behind the numbers 2025. Retrieved March 20, 2025, from https://www.pwc.com/us/en/industries/health-industries/library/behind-the-numbers.html.

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