Research Article

Industry Mix as a Place-Level Heat Risk Indicator: Outdoor-Labor Share and Heat-Related Emergency Department Visit Rates in Virginia, 2025

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ABSTRACT

Extreme heat increases emergency department (ED) utilization. However, there are only a few place-level studies conducted to see whether industry mix in a community may signal vulnerability to extreme heat. This study specifically seeks to answer whether localities in Virginia with a higher outdoor-labor employment share tend to experience higher rates of heat-related illness (HRI) emergency department (ED) visit. This study hypothesized that localities with higher outdoor-labor share may have higher heat-related illness ED visit rates. Two datasets: Virginia Department of Health locality HRI counts (VHD HRI, year 2025) and Bureau of Labor Statistics (BLS) Quarterly Census of Employment and Wages (QCEW, 2023) were merged to generate outdoor-labor share (construction + natural resources & mining) / All private industries. Records with jurisdictions combined by VDH were retained, and labels were programmatically split and allocated with HRI counts in proportion to QCEW "All industries" employment in each component and rounded with integers. 114 unique localities (with 125 complete-case entries) were included in the analytic datasets. The primary model was Poisson generalized linear model applied with log link and log(QCEW "All industries") size offset. Incidence rate ratios (IRRs) were estimated per 10-percentage-point increase in outdoor-labor share with standard errors. With the Poisson (offset) estimates, the hypothesis in this study was supported. IRR was 1.60 (95% confidence interval 1.10-2.33, $p=0.013$). A Negative Binomial sensitivity with Akaike Information Criterion-selected dispersion ($\alpha \approx 0.93$) was directionally positive but less precise. IRR was 1.21 (95% confidence interval 0.96-1.53, $p=0.104$). The ecological (place-level) analysis in this study suggests that industry structure can inform targeting of heat-health prevention.

Keywords: Heat-related illness; Emergency department visits; Outdoor labor; Construction; Wet-Bulb Globe Temperature (WBGT); Virginia

INTRODUCTION

Extreme heat has been a growing concern in public-health area in the United States. In 2023, a prolonged, region-wide increase in the heat-related emergency department (ED) visits was witnessed (1-3). Among many other states, Virginia provides data for local-level

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heat-related illness (HRI) counts for ecological analysis (4). Local industry composition, a structural determinant for heat-related illness emergency department visits beyond the causes from meteorology and demographics has a potential in influencing morbidity from heat through greater outdoor exposure, such as construction, natural resources, or mining (5-9). This mechanism has been underscored by occupational safety guidance, including WBGT-based limits and national emphasis programs (6, 7). However, it has remained understudied as to how this could be influenced by population-level place indicators from industry mix.

The relation between heat exposure in relation to occupational morbidity and injury has been actively researched. According to the national evaluation, it was concluded that WBGT-based limits were exceeded in most non-fatal illness-related cases among outdoor workers as well as all investigated fatalities under similar environments. Therefore, a Heat Index screening threshold of around 85°F was suggested when WBGT was not available (10). A substantial burden of occupational injuries from extreme temperatures was estimated by a multicounty analysis (11). Consistent associations between heat and traumatic injuries were also reported from reviews along with possible physiologic and cognitive pathways (12, 13). Furthermore, a record-breaking heat wave has caused a dramatic increase in ED visits as reported during the 2021 Pacific Northwest dome (14). In addition, occupational heat fatalities were reported by the U.S. Environmental Protection Agency (EPA) over multiple decades, indicating that about one-third of deaths occurred at the construction sites and therefore emphasizing the relevance of outdoor-labor workload intensity in the perspective of public health (15). Dealing with these issues, heat-risk tools have continued to develop for better decision making process. For example, the CDC Heat & Health Tracker was generated to provide syndromic trend, and the National Weather Service HeatRisk has been providing location-specific risk guidance utilized as a sign of warning with heat by many agencies or employers (16).

In spite of growing literature about health concern from extreme heat, there remains a notable gap in place-level (ecological) researches that particularly link local industry heat related illness to population-level. Most prior studies conducted for heat related illness modeled meteorology, demographic vulnerability, or injury risk for particular cohorts of workers. There were only a few studies researching locality-based industry data that were publicly available to be merged for testing if communities with higher outdoor-labor employment had more experience with higher heat-related illness emergency department rate. This remained a question requiring immediate implications for heat-related illness prevention standards.

This study addresses the aforementioned literature gap by testing whether localities in Virginia with higher outdoor-labor employment shares had an experience of higher heat-related illness emergency department visit rates by using publicly available VDH HRI counts (2025) and BLS QCEW (2023). A Poisson generalized linear model was pre-specified with a log size offset, while reporting incidence-rate ratios (IRRs) per an increase of 10-percentage-point (pp) in outdoor-labor share. In addition, a negative binomial sensitivity was fit to assess over-dispersion.

This study particularly seeks to answer whether communities (at the locality level) with a higher outdoor-labor employment in Virginia experience higher heat-related illness ED visit rates after considering locality size. I leverage two public sources (VDH locality heat-related illness counts; BLS QCEW employment) that are aligned with priorities in occupational-heat prevention in an attempt to provide actionable insights for preparedness for extreme heat conditions.

This study hypothesized that communities (at the locality level) with a higher outdoor-labor employment would experience higher heat-related illness ED visit rates (per capita), compared to the communities with lower outdoor-labor employment. This hypothesis followed an expectation from occupational-heat evidence (outdoor work associated with greater physiologic and environmental heat loads) and also from the broad impact of heat on acute health-care utilization (1, 10, 15).

METHODS AND MATERIALS

Study Design

A cross-sectional and ecological study was conducted for Virginia localities, including counties and independent cities, to test if communities with a higher outdoor-labor employment tend to experience higher heat-related illness ED visit rates. Two publicly available data sources were used for the analysis: VDH locality-level heat-related illness dataset and the Bureau of Labor Statistics (BLS) Quarterly Census of Employment and Wages (QCEW) 2023 county-level high-level industry workbook. The VDH locality-level

HRI dataset provided annual ED visit counts from heat-related illness, along with locality labels and years, and the BLS QCEW 2023 datasets reported data for employment of high-level NAIC "supersectors," including 1011 Natural resources & mining, 1012 Construction, and 10 All industries. Particularly, outdoor-labor employment share from BLS QCEW 2023 (construction + natural resources & mining divided by All private industries) was constructed. Then, a pre-outcome (lagged) exposure year was used to represent baseline industrial structure of each locality for the year 2025 outcome. County-level industry composition tended to change slowly over short time period. Therefore, QCEW 2023 was a reasonable proxy used for the year 2025 while preserving temporal precedence.

Outdoor-labor employment share was calculated using the following formula:

$$\text{OutdoorShare}_i = \frac{\text{Employment}_{1011,i} - \text{Employment}_{1012,i}}{\text{Employment}_{10,i}}$$

Where i is the index of a county/city in Virginia, and the rate base is All private industries. A great portion of occupations identified by these two supersectors were either outdoors or in partially conditioned environment.

Merging VDH locality names to QCEW county names through (i) city vs. county suffixes, (ii) Virginia postfix in QCEW's area names, and (iii) VDH rows by combining multiple jurisdictions in a single label took two steps. First of all, the term "Virginia" was removed while lowercasing names, and also taking trailing city and county out. Then, single-jurisdiction records were matched by using this normalized key by merging VDH to QCEW. In addition, for any VDH label with the jurisdiction containing "and" or multiple comma-separated parts, the label was split into its component jurisdiction (e.g. "Fairfax City," "Falls Church City," and etc.) Then, the heat-related illness counts were allocated to components in proportion to QCEW of each component in "All industries" employment. Without dropping combined VHD rows, strings were split in Python, while allocating ED visits counts proportionally to the same employment quantity that was used in the model offset to preserve the same information and internal consistency between rate estimation and allocation. When there was no non-zero employment in all components, equal weights were applied. Then, all allocated counts were rounded to the nearest integer to keep a discrete outcome. It was also assured that the sum of allocations across components was exactly same as the original combined total. With these steps, one-predictor model was established. Outdoor-labor share and size offset were used to satisfy the two-file constraint. A log size offset based on QCEW "All industries" employment was used to estimate rates, while utilizing a one-predictor specification (outdoor-labor share) to reflect the two-file design. No additional covariates were included in the primary models.

The annual count of heat-related illness ED visits per locality was the outcome in this study. Since raw counts were scaled with locality size, a rate was used as an estimand. Using two-file constraint, log(QCEW "All industries" employment) was used as a size offset as follows:

$$LogE[HRI_i] = \alpha + \beta \cdot OutdoorShare_i + \log(Employment_{10,i})$$

With this formula an incidence rate ratio (IRR) was calculated for outdoor-labor share.

Statistical Analysis

After summarizing the number of unique localities (city/county) and the entire rows through splitting/allocation of computed labels, the distribution of outcome and exposure was examined. What was anticipated was variance to exceed the mean since most administrative count data were right skewed.

After scaling the outcome and offsetting the size from the datasets, This study fit a Poisson generalized linear model with log link and the log employment offset. The coefficient (β) of an OutdoorShare was reported as IRR, and the effect of it was presented per 10-percentage-point (pp) increase in outdoor-labor share for the interpretability. Therefore, . In addition, heteroskedasticity-robust (sandwich/HC) standard errors were used to analyze data against mild model misspecification. To deal with possible overdispersion, This study fit a Negative Binomial (NB2) GLM with the same offset. Since specification of dispersion was required by several GLM-NB implementations, The α parameter was selected by minimizing Akaike Information Criterion over plausible values. Then, IRR per 10-pp was reported again for comparability. Python was used to deal with exposure construction from QCEW and split and allocate labels, and merge and model the datasets with standard scientific libraries.

RESULTS

In the data analysis procedure, the analytic dataset contained 114 unique localities (including 125 complete-case rows when calculating entries in locality-year in the model) for the year 2025 after harmonizing and splitting/allocating combined VDH labels. A significant portion of localities were included under a one-to-one mapping. Right skewed distribution was shown in the distribution of heat-related illness counts, and there was an upward trend in the heat-related illness rate per 10,000 employees against outdoor-labor share. The mean rates increased across outdoor-share quartiles. This pattern was consistent with the hypothesis established in this study (Table 1).

Poisson GLM with size offset

The pre-specified primary model established with Poisson with log link and log(QCEW "All industries" employment) as the size offset reported a statistically significant positive relationship between outdoor-labor share and heat-related illness rates. IRR per +10 percentage points outdoor-labor share was calculated to be 1.60 (95% confidence interval 1.10 – 2.33; p=0.013). The rate specification was higher than a counts-only Poisson without offset from Akaike Information Criterion (AIC). The Pearson χ^2/df was greater than 1, showing overdispersion that was addressed with strict standard errors and a negative binomial sensitivity.

With the variable for size offset, locality size was held constant such that a locality within a 10pp higher outdoor-labor employment share was estimated to experience heat-related illness ED visit rates that were 60% higher than the ones with a lower share. When the size offset was not included, the counts-scale model provided a negative relationship between outdoor-labor share and heat-related illness rate due to a rate base (size-scaling) issue: fewer residents in small localities with higher outdoor-share and also fewer ED visits in small sized localities than large urban localities.

Negative Binomial Sensitivity

In order to evaluate the model fit under overdispersion, This study fit an NB2 model with the same size offset and selected dispersion by Akaike Information Criterion. The NB estimate was calculated to be directionally positive but wider in interval as IRR per +10pp was calculated to be 1.21 (95% confidence interval 0.96-1.53, p=0.104; AIC-selected dispersion $\alpha \approx 0.93$). For completeness, Poisson (offset) and NB2 (offset) AICs were reported (Table 2).

With the modest locality level sample size, evident dispersion and wider intervals of estimates were anticipated and actually confirmed to align with the Poisson estimates. The directional positive association between outdoor-labor share and heat-related illness rates across models reinforce the outdoor-labor intensity as a place-level indicator for heat morbidity.

These findings were also visually confirmed that

Table 1. Descriptive (Virginia). Descriptive statistics for localities in Virginia, 2025 (N=114 localities, 125 complete-case rows)

	Measure	Min	P25	Median	P75	Max
1	N Localities (unique)	114.0				
2	Complete-case rows	125.0				
3	HRI ED Visits (count)	2.0	7.0	14.0	29.0	158.0
4	Outdoor-labor share (Construction + NatRes/Mining / All)	0.0	0.048	0.077	0.122	0.424
5	QCEW 'All industries' employment (size proxy)	1347.0	3223	8851	23893	544515
6	HRI ED visits per 10,000 employees	0.58	10.13	15.82	25.58	928.87

Values of HRI ED visits (count), outdoor-labor employment share, QCEW "All industries" employment (size proxy), and HRI ED visits per 10,000 employees were reported as min, median, IQR, max, and mean as noted.

Table 2. (Models, IRR Per +10pp). Regression results for locality-level HRI ED visit rates in Virginia, 2025

	Model	IRR per +10pp	95% CI Lower	95% CI Upper	p-value	AIC	Pearson χ^2/df	Alpha (NB Only)
1	Poisson (log size offset)	1.60	1.10	2.33	0.013	4504	139.55	
2	Negative Binomial (log size offset)	1.21	0.96	1.53	0.106	1088		0.93

scatter of heat-related illness rate per 10,000 employees vs. outdoor-labor share showed an upward slope in an ordinary least squares reference line (Figure 1). The mean heat-related illness rate per 10,000 employees across quartiles (Q1-Q4) of outdoor-labor share increased from lower to higher quartiles, while outlier influence was reduced (Figure 2). In addition, the IRR per +10pp and its 95% confidence interval were also reported with observed vs. predicted counts from Poisson offset model, while points aligned well along 45° line across local units (Figure 3).

DISCUSSION

This study investigated whether places with higher outdoor-labor employment tended to experience higher heat-related illness (HRI) emergency department (ED) visits. Utilizing two publicly available datasets and a

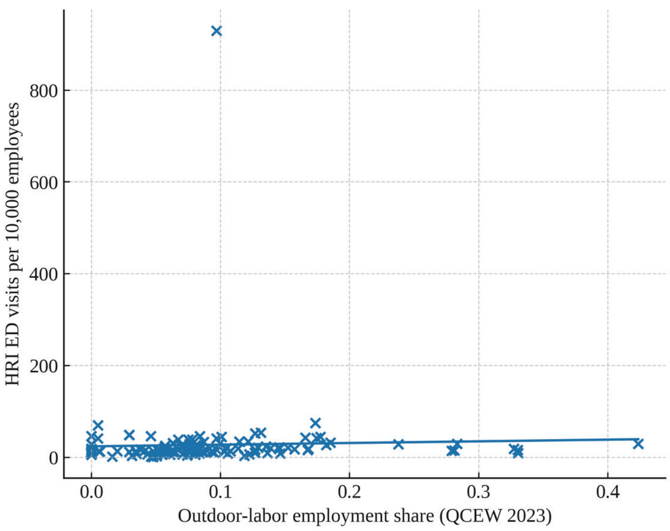

Figure 1. HRI ED Visits Per 10,000 Employees vs. Outdoor-Labor Share (Virginia, 2025). Figure shows scatterplot of heat-related illness emergency department visits per 10,000 employees in localities (y-axis) against outdoor-labor employment share calculated by dividing (construction + natural resources and mining) by all private industries from BLS QCEW 2023 (x-axis). N = 114 unique localities (125 complete-case rows after splitting and allocating combined VDH labels). The positive gradient was visualized from an ordinary-least-squares reference line. Outcome counts were from VDH locality heat-related illness (2025). Employment denominators were from "All industries" from QCEW. Finally, rates were calculated per 10,000 employees.

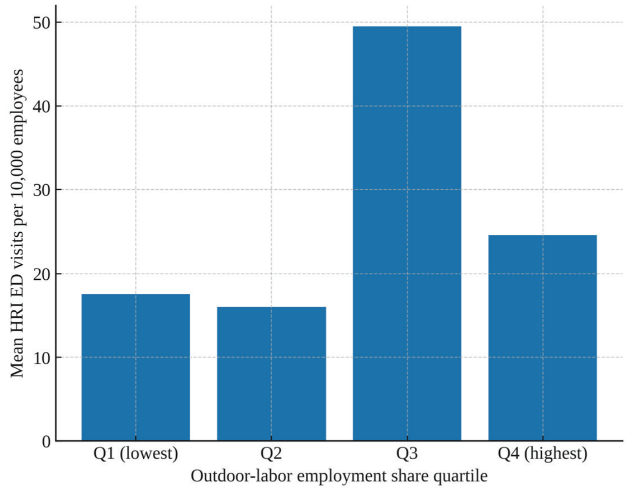

Figure 2. Mean HRI ED Rate Per 10,000 Employees by Quartile of Outdoor-Labor Share. The mean heat-related illness emergency department visit rate across quartiles (Q1-Q4) of outdoor-labor share was calculated from QCEW 2023 to construct bar plots. Quartiles were defined for all 114 localities. The mean and 95% confidence interval of the rate were reported within each quartile. Outlier influence related to the raw scatter reduced.

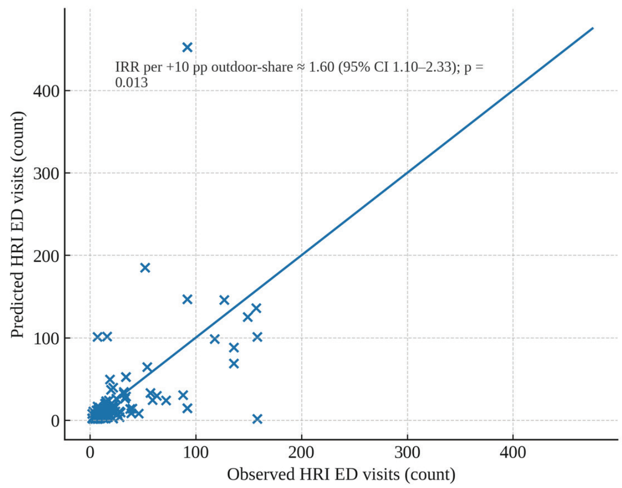

Figure 3. Observed vs. Predicted HRI ED Visits from the Poisson Rate Model with Log Size Offset. Each point on the graph represents a locality (N = 125 complete-case rows). The x-axis represents observed annual heat-related illness emergency department visit counts, while y-axis represents model-predicted counts from the Poisson generalized linear model with log link and log (QCEW "All industries") employment offset. The 45-degree line shows perfect agreement. Coefficient on outdoor-labor share in the model is reported as an IRR per + 10 pp (IRR = 1.60; 95% confidence interval 1.10-2.23; p=0.013).

transparent workflow, this study found that local units (city/county) in Virginia with higher outdoor-labor employment actually had higher heat-related illness ED visit rates in 2025. With pre-specified Poisson model with the size offset, a 10-percentage-point (pp) increase in outdoor-labor share led to about heat-related illness rates that were 60% higher than the ones with lower outdoor-labor employment (incidence-rate ratio [IRR] 1.60; 95% confidence interval 1.10-2.33; $p=0.013$). A negative binomial (NB2) sensitivity with dispersion selected by AIC was directionally consistent but less precise (IRR per +10pp 1.21; 95% confidence interval 0.96-1.53; $p=0.104$; $\alpha \approx 0.93$). Put all of these results together, the study hypothesis was supported, even though it signaled the uncertainty about overdispersed count and modest sample sizes.

Both the direction and magnitude of the primary rate estimate was consistent with established occupational-heat dynamics and prior evidence about heat morbidity and injuries among outdoor laborers. Occupations in construction and natural resources/mining had greater exposure to metabolic heat, limited environmental controls, and radiant load that played a role of possible short-term heat-related illness risk factor during hot seasons. Place-level approach take in this study did not identify heat-risk illness rate at an individual worker-level but analyzed the structure of a local economy with special focus on a higher outdoor-labor share as a useful indicator for population vulnerability to extreme heat. Given how the counts-only model without a size offset provided a negative association between outdoor-labor employment and heat-related illness ED visit rates and underscored problems such as smaller rural areas with higher outdoor-labor share but with fewer ED visits from heat-related illness, the model in this study employing an offset variable was essential for comparisons across places.

Using only two publicly available datasets: locality heat-related illness counts from VHD and BLS QCEW employment, this study made it convenient to reproduce datasets available for the analysis. In addition, this study combined jurisdictions (county + independent city) through VDH records as locality analysis, programmatically split and allocate labels and heat-related illness counts in proportion to QCEW "All industries" employment of each component, and ultimately yielded a total of 114 unique localities for the year 2025. Lastly, a pre-specified rate was used to examine overdispersion through a negative binomial sensitivity by selecting data-driven dispersion, and it pointed to the same direction as indicated in the primary model.

Limitations

While this study provides place-level evidence of a relation between outdoor-labor employment and heat-related illness emergency department visit rates in Virginia, there are limitations for external validity. First, this study has calculated estimates based on place-level association that may not be interpreted in the same way for causal-effect at an individual worker level. Second, this study has specifically applied two-file constraint with QCEW "All industries" employment as the size offset. This analytic approach may be good for a structural exposure with industry mix, but preferred rate base was the population for per-capita rates. Therefore, when a population offset is available to use, a follow-up may be needed to interpret magnitude calculated in this study. Third, this study measured outdoor-labor share in 2023 and applied the results to outcomes in the year 2025 as a lagged exposure. This was because of slow changes seen in industry composition at the national level, and QCEW 2023 was a reasonable proxy for baseline structure. Lastly, this study used syndromic outcome. Heat-related illness counts from emergency department were based not on disease incidence but on utilization that coverage may be different with facility participation.

Although this study focused on Virginia, the analytic approach may be applied to other places if similar data are available to use. The findings in this study must be interpreted as Virginia-specific until replicated, as different jurisdictions vary with climate conditions, healthcare access, and data participation. In addition, there is still a possibility for other sub-sectors (e.g., oil and gas and agricultural) to have varied conditions in terms of baseline acclimatization or cooling infrastructure.

With aforementioned limitations in this study, it is suggested for future research to substitute population for employment in the offset to calculate per-capita rates directly. This is expected to narrow uncertainty without changing the qualitative conclusion of the study. In addition, it is also recommended to add one meteorology covariate to explain the differences between localities with heat exposure in 2025 for industry mix.

CONCLUSION

Using two public datasets, this study tested if industry mix in a locality signals vulnerability to extreme heat. After harmonizing HRI counts of localities in Virginia and programmatically splitting/allocating labels, this study analyzed 114 localities (2025). With a log size effect, Poisson rate model was applied based on QCEW "All industries" employment, finding that a 10-percent-point increase in outdoor-labor share was associated with a 60% higher heat-related illness emergency department visit rate (IRR 1.60, 95% confidence interval 1.10-2.33, p=0.013). A negative binomial sensitivity (α ≈ 0.93) was directionally positive but less precise (IRR 1.21, 95% confidence interval 0.96-1.53, p=0.104). Ecological analysis was performed to show the results, but these findings shall not be interpreted at individual level effects. In addition, employment was used as a rate base rather than population. However, consistent gradient implies that industry structure may play a role of guiding heat-related health preparedness, while prioritizing employer engagement and securing proper resources for high-outdoor-labor localities.

CONFLICT OF INTEREST

The author declares no conflicts of interest related to this work.

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