Impact of the 2019 Kincade Wildfire in Sonoma County, California

on Emergency Room Visitations

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ABSTRACT

The effects of anthropogenic climate change are causing annual wildfires in California to become more frequent and widespread, increasing exposures to fine particulate matter, the most dangerous air pollutant associated with wildfire smoke. The main focus of this study was to identify the effects of a major California wildfire on cardiovascular and respiratory emergency room visits, with secondary analysis conducted on obstetric, cerebrovascular, and psychological ER visits. We analyzed the dose response relationship between wildfire smoke from the Kincade Fire of 2019 and negative public health outcomes using de-identified emergency room (ER) visit data from Sonoma County, along with smoke plume data from the National Oceanic and Atmospheric Administration. We found that both during and following the fire there was an increase (though not statistically significant) in the odds of respiratory ER visits in Sonoma County (19%) during and (75%) after (p-value of 0.71 and 0.28 respectively). Additionally, there was a statistically significant trend found between increasing smoke plume density and the relative risk of respiratory ER visits (31.1% increase in risk going from no smoke plume to a high smoke plume density, p-value of 0.01).

INTRODUCTION

Anthropogenic climate change is defined as the change in the natural environment that is a direct result of human activity. This has been observed throughout history, from deforestation, the introduction of foreign agriculture in natural spaces, the disturbance of natural landscapes for human settlements, and other changes. Since the Industrial Revolution, humans have also changed the climate as a result of the emission of greenhouse gasses, precursors of greenhouse gasses, and aerosols (Masson-Delmotte, n.d.). This has occurred mainly through the burning of fossil fuels, such as coal and oil, which release large amounts of greenhouse gasses after combustion. One of the most abundant greenhouse gasses is carbon dioxide, which has a large impact on the greenhouse effect. The greenhouse effect causes the Earth's atmosphere to trap heat from the Sun's energy instead of allowing it to be released into space. Since the industrial revolution, carbon dioxide levels have unnaturally increased to upwards of 417 ppm in 2021 (Betts, n.d.). These higher carbon dioxide levels, along with increases in the levels of other greenhouse gasses, have caused warming and induced many unnatural changes to the natural environment. This change in weather pattern as a result of anthropogenic climate change is of greatest interest in regards to this particular paper.

Wildfires have been a perennial problem for the people of the Western United States and notably California. The record of California wildfires dates back to 1932, but the region has experienced wildfires for much longer than that. This occurrence has to do with the weather pattern. The majority of the moisture occurs in the fall and winter, and during the rest of the seasons there is a lack of rainfall. This causes vegetation to dry out and serve as fuel for fires (Pierre-Louis & Schwartz, 2021). This dry vegetation alone is not sufficient to create a wildfire, there needs to be a combination of warm temperatures and low moisture, in order for a spark to start a fire. The combination of these warm and dry conditions creates a "fire season", which has historically occurred during the hotter summer months. However, the effects of anthropogenic climate change have caused extended periods of low precipitation to occur concurrently with warmer temperatures,which has increased the duration of wildfire conditions into the autumn months, resulting in more California wildfires.

Another reason for the multitude of wildfires in California, is that the effects of anthropogenic climate change have also resulted in more frequent and intense drought conditions. Previous analyses (Diffenbaugh et al., 2015) show that "California has historically been more likely to experience drought if precipitation deficits co-occur with warm conditions". This trend is additionally proven by the fact that in the past four decades, California has seen a drop in autumn precipitation by almost 30% (Goss et al., 2020). The U.S Drought Monitor, a program of the National Oceanic and Atmospheric Administration(NOAA), has created a framework to study the extent of droughts in California. Since the creation of this program in 2000 and the monitoring of California began, there have been six years where there were little to no moderate drought or worse conditions (2000, 2005, 2006, 2011, 2019). The longest span of continuous drought lasted 376 weeks beginning on December 27, 2011 and ending on March 5th, 2019, with the worst period of drought occurring the week of July 29, 2014 where exceptional drought conditions affected 58.41% of California. (*California*, n.d.)

Studies show this correlation of low precipitation and increased temperatures is directly caused by anthropogenic warming. The greenhouse effect has been shown to increase global temperatures, and these effects are visible in California. Since 1972, summer temperatures in California have increased by an average of 1.4 ^{o}C (Williams et al., 2019), and average autumn temperatures have increased by around 1^{o}C (Goss et al., 2020). Climate models of anthropogenic warming also show that these hotter and drier conditions are expected to continue, "additional global warming over the next few decades will result in ~100% probability that the annual dry period is extremely warm" (Diffenbaugh et al., 2015). Anthropogenic climate change is causing

California to have more periods of high heat and low precipitation, and as it continues, the wildfire seasons will continue to worsen.

Anthropogenic climate change has caused an increase in the severity and extent of wildfires. In the past century, the danger caused by wildfires has increased as the number and extent of wildfires have increased significantly. Since the 1980s the number of autumn days with extreme fire weather, defined as the probability of fires starting or growing in the 95th percentile, have more than doubled (Goss et al., 2020). Additionally, from 1972-2018 there was an eightfold increase in acreage that summer forest fires extended (Williams et al., 2019)**.** This growth can also be seen in individual fires, where the past decade has had some of the largest wildfires by acreage ever recorded. Of the 20 largest California wildfires in recorded history, 14 have occurred since 2012, while the seven largest wildfires have occurred since 2018. The worst wildfire season in history occurred in 2020, when 4,257,863 acres were burned by wildfire, double the acreage of the previous worst season (*2020 Fire Season | Welcome to CAL FIRE*, n.d.). In comparison, 2019 was a more mild wildfire season, as 7,860 wildfires burned a total of 259,823 acres (*2019 Fire Season | Welcome to CAL FIRE*, n.d.). Despite this lighter year, there is still a worrying trend of increasing wildfires' extent, which poses many dangers to populations nearby.

This study will focus on the specific effects of the 2019 “Kincade Fire”. The wildfire started on October 23rd, 2019 and was contained on November 6th, 2019. This wildfire burned exclusively in Sonoma county, and extended to 77,758 acres of land. As a result, it was the single largest fire in terms of extent during the 2019 wildfire season. The resulting smoke cloud was detected in every county in the state and the fire caused the evacuations of over 186,000 residents. ("Kincade Fire Evacuation Orders," n.d.).

Wildfires expose the people of California to many dangers, mainly the threats to human health in the smoke cloud of wildfires. The burning of vegetation and man made items that occurs during a wildfire release hazardous air pollutants such as: carbon monoxide, nitrogen dioxide, ozone, polycyclic aromatic hydrocarbons, particulate matter (PM), among other dangerous pollutants (Reid Colleen E. et al., 2016). Exposure to these pollutants are hazardous to human health as they have been significantly associated with the risk of respiratory and cardiovascular illness (Liu et al., 2015). This paper will focus on the acute effects of wildfire smoke.

The most dangerous pollutant in wildfire smoke is particulate matter (US EPA, 2019). Particulate matter pollution is the term for exceedingly small solid and liquid droplets, which pose a health risk because they can be easily inhaled. There are two main types of particulate matter pollution, coarse particulate matter ($PM_{2.5-10}$) which are particles with diameters that range between 2.5 and 10 micrometers, and are a small portion of wildfire smoke. Along with fine particulate matter ($PM_{2.5}$) which is an air pollutant composed of tiny particles (2.5 micrometers or smaller in diameter). Fine particulate matter is one of the main pollutants emitted from wildfire smoke, and comprise approximately 90% of the total particle mass of wildfire smoke (Vicente et al., 2013).

The World Health Organization has estimated that PM pollution has contributed to approximately 4.2 million premature deaths each year, making it one of the leading causes of mortality worldwide (*Data Review*, n.d.). The health effects of long term exposure to PM have been widely studied, with associations to increased hospitalization for asthma, increased urgent care visits for cardiopulmonary issues, and increased mortality. (Landguth et al., 2020). Recent studies have begun exploring the short term effects of PM pollution as a result of wildfire smoke, and have found that there is a significant association with negative respiratory effects as a result of exposure (Landguth et al., 2020). The small particles associated with PM pollution triggers pulmonary oxidative stress and inflammation once they enter the lungs (Anderson et al., 2012), resulting in a decline in lung function and causing increases in ER hospitalizations for respiratory issues. There have been multiple studies that have shown wildfire smoke exposures exacerbates the effects of asthma leading to a statistically significant increase in hospitalizations (Landguth et al., 2020). Additionally, it elevates the rates of hospitalizations for patients with Chronic Obstructive Pulmonary Disease (COPD). (Reid Colleen E. et al., 2016) PM pollution has been shown to contribute to cardiovascular and cerebrovascular disease through systemic inflammation, direct and indirect coagulation activation, and direct translocation into systemic circulation (Anderson et al., 2012; Jones et al., 2020). A review of previous studies found that a short term 10 $\mu g/m^3$ increase in PM caused a significant increase in hospitalizations for congestive heart failure and heart disease (Morris, 2001).

Additionally, there have been studies that have shown with high certainty that there is an association between particulate matter exposure and poor birth outcomes. A study conducted in Brazil found that exposure to air pollution during the second and third trimesters of pregnancy was associated with newborns having low birth weight (Cândido da Silva et al., 2014). Additionally, a review of seven studies on the effects of wildfire smoke exposure on pregnant women found that six of the studies observed an association between exposures and a reduction in birth weight (Amjad et al., 2021). This is an issue because babies with a low birth weight have a greater risk of developing medical problems, such as having a harder time eating, fighting infections, and gaining weight. Additionally, many babies born with low birth weight are premature, which can cause additional complications (*Very Low Birth Rate*, n.d.).

Along with the physical health impact of wildfires, there are also measured psychological tolls. Children are especially vulnerable to the negative psychological impacts of natural disasters. Viewing a traumatic event, such as a wildfire, in close proximity to a child's home is a major cause of emotional distress. (Ducy & Stough, 2021). A study of the 2011 Slave Lake wildfire in Canada found 14-54% of children that had been evacuated met or exceeded the threshold for PTSD symptoms (Townshend et al., 2015). Another study done in Northern California found that exposure to wildfires caused feelings of loss, grief, and trauma in children with disabilities (Ducy & Stough, 2021).

Californians are especially exposed to the danger of PM pollution; between 2007-2013 97.4% of California's population lived in a county that experienced smokewave conditions (over 35 $\mu g/m^3$ for more than two consecutive days) (Koman et al., 2019). This is over twice the EPA standard for acceptable levels of particulate matter pollution, that is set at 12 $\mu g/m^3$ and 15 $\mu g/m^3$ (US EPA, 2016). As the extent of California that wildfires cover continues to grow, more of the population will be exposed to these dangerous conditions.

This study specifically focuses on the respiratory and cardiovascular health effects of the Kincade wildfire, testing the hypothesis that exposure to wildfires can lead to an increase in short-term emergency room visits. Additionally, this study estimates the effects of increasing smoke plume densities. Due to the availability of data, secondary analyses were also conducted to identify the effect on cerebrovascular, obstetric, and psychological emergency room visits.

METHODS

DATA SOURCES

The first aspect of this project was to determine the extent of the smoke plume from the Kincade fire. This knowledge would be used to determine how much the smoke plumes affected Sonoma County, and additionally identify counties that were less affected and could serve as a suitable control for comparison. The extent of the smoke plumes was mapped using the NOAA hazard mapping system (NOAA, n.d.). This dataset consists of daily plume boundaries as detected by Geostationary Operational Environmental Satellite imagery, along with the density of the smoke plume (none/light/medium/high). This dataset was overlaid on a breakdown of all of the zipcodes in California from the start of October to the end of November, since the Kincade fire was specifically from October 23rd to November 6th.

The health outcome dataset for this study was taken from Emergency Room utilization data provided by the California Office of HealthCare Access and Information (HCAI) for this study via the Sonoma County District Attorney's Office. It contained de-identified data from Californian hospitals for the entire month of October until November 10th. It included all individual ER visits, patient age, sex, residential zip code, and primary and secondary ICD-10 codes (International Classification of Diseases, Tenth Revision, Clinical Modification).

EXPOSURE AND OUTCOME

The first step in tracking exposure was to define the different firetimes. It is public record that the Kincade Fire lasted from October 23rd to November 6th. Since the data encompassed more time than this: the 14 days prior to the fire were defined as the *before* firetime, the 14 days during the fire were defined as such, and the following four days were the *after* firetime. The next step was to decide which exposure variables would allow examination of the true extent of the Kincade smoke plumes. The NOAA dataset contains variables for the amount of smoke in a residential zip code at any given day based on the density of the smoke plume. These low, medium, and high count variables for both the Kincade fire and other fires tell how much smoke affects the zip code on a day by day basis. All of these counts are distilled down into two main variables that allow tracking of the smoke plume.

The health outcome dataset was entirely composed of ICD-10 codes that are specific to billing codes, at a level of granularity greater than needed for our analysis. In order for them to be analyzed they were categorized into groups based on what main disease group was involved. Based on the literature review conducted before this study began, it was known that there are respiratory, cardiovascular, and cerebrovascular issues caused by wildfire smoke. It was also decided that it would be of interest to also see if there were obstetric (pregnancy) and psychological effects, so they were also added to the study. The groups were composed of the following ICD-10 codes. Cardiovascular: I10-I16, I20-I28, I30, I40, I42, I 44-51, I70-I72, I74, I75, I77, I79, R00, R07. Cerebrovascular: I60-69, G45-46. Respiratory: J00-J99, R04-R06, R09. Obstetric/Pregnancy-Related: O00-O08, O10-O16, O20-O29, O60-O77. Psychiatric: F20-F48. Furthermore, specific diseases of interest within these disease groups were also identified using ICD-10 codes. Myocardial Infarction, Ischemia/Angina, Chest Pain: I20-25, R07. Cardiac Arrest: I46. Heart Failure: I50. Asthma: J45-46. COPD (obstructive pulmonary disease): J40-44. Miscarriage: O00-O08.

DATA CLEANING AND MANAGEMENT

In order to clean the NOAA dataset, the sets of zip codes were grouped into their respective counties via a dataset containing all the residential zip codes in America and their respective counties. This dataset was then merged with the original NOAA dataset and a new variable was created that had all of the zip codes grouped into counties. The next step was to see how many smoke days there were in all of the counties. Using R Studio, a new dataset was created that returned the sum of all smoke day occurrences caused by the Kincade fire by counties. Another that returned the sum of all the occurrences of a smoke day caused by a different fire, and a third that was the sum of both of these datasets when combined (Figure 1). This was created in order to identify a suitable control county.

The first iteration of searching for a control county was to create a function in R Studio to look at which counties had no smoke day occurrences for either the Kincade or other fires. This function discovered that Alpine, Del Norte, Inyo, Lassen, Modoc, Mono, Plumas, Shasta, Sierra, Siskiyou, Tehama, and Trinity County had the lowest number of smoke days recorded. These counties (except Shasta) were not good possibilities for a control county. With the exception of

Shasta County, all of these other counties had populations that were under 66,000 people. Given the size of Sonoma County was over 480,000 people, these smaller counties were deemed not to be a good comparison.

The next iteration was to look at all 23 counties in California that were over 400,000 people. This number was selected because Sonoma County had a population of 488,863 people according to the 2020 Census (*U.S. Census Bureau QuickFacts*, n.d.). In order to reduce confounding variables, a county of similar size needed to be studied. There are 23 counties in California that had a population of over 400,000 people, and another control county possibility was added in Shasta County. Of these 24 possible counties, 17 had lower average smoke day occurrences than the 10.36 average for Sonoma County (Figure 2). Of these 17 counties, only those with an average smoke occurrence count of less than half of 10.36 were considered. As a result, only San Bernardino (2.37), Riverside (2.7), Shasta (3.27), San Diego (4.22), Orange (4.83), and Kern (4.88) County were considered.

Due to the many differences in demographics in counties in California, there were other benchmarks that a suitable control county would need to meet. There was no specific variable range that was considered but it was important that the county have a similar median age, percentage of the population over 65 years, socioeconomic status, ethnicity, and low smoke exposure. As per Figure 2, the county that best met all of these criteria was Shasta County. Its similarities in median age (41 vs 43.1 for Sonoma), percentage of the population over 65 (20.2 compared to 19) and demographics meant that there would be less confounding variables to impact the data. San Bernardino, Riverside, and Kern were also identified as possible control counties primarily based on the low number of smoke plume exposure days compared to Sonoma County.

The HCAI data also required transformation. The de-identified data was in the long form of the data, meaning that every time an individual was seen at the ER in any capacity that they were recorded. If an individual was moved around the hospital, they would have a separate datapoint each time they were in a new department. In order to avoid problems in analysis, the data was transformed to combine all patients that had the same date of admittance and zip code of origin into a single data point. It was also truncated to match the timeframe of the NOAA dataset. Complete case analysis was used to handle an missing data.

In order to conduct analysis to determine the effect of different smoke plume densities, the HCAI de-identified data had to be merged with the NOAA data of the densities of the different smoke plumes. The only smoke day variables of interest were the level of Kincade fire smoke, which was recoded to a three-level ordinal variable (none/ low-medium/ high). Then, the same processes that were used for cleaning the Sonoma County NOAA and HCAI data were applied to the control county of Shasta County.

STATISTICAL ANALYSIS

Initial data analysis was performed to observe the number of each disease category and the specific diseases of interest. For both Sonoma and Shasta County, charts were generated to obtain a visual representation of the total number of hospital admissions based on disease group and the specific diseases of interest. Due to the discrepancy in studied days with only four after the fire, the proportions of daily ER visits by each disease group and specific diseases were identified. From this a surface level comparison was done to see if there were observable changes in ER visits before, during, and after the fire (Figures 3-6).

The next analysis was a time series that allowed the examination of the effects of the fire on ER visits before, during, and after the fire had passed. It was determined that a logistic regression model would be suitable for analyzing the change in ER visits due to firetime (before/during/after) based on individual diseases, due to the model's ability to assess ER visits as binary outcomes. A logistic regression model was created for both Sonoma and Shasta County, and run separately on each disease group. It was not performed on the specific diseases because their numbers were too few to have sufficient statistical power. This produced the coefficients of the log odds of the increase in each disease group (Respiratory, Cardiovascular, Cerebrovascular, Obstetric, and Psychiatric) during and after the fire in comparison to before the fire. These coefficients then had to be exponentiated in order to obtain the odds ratios of ER visits for these diseases during different fire times compared to the pre-fire timeframe. A 95% confidence interval of the odds ratio was also calculated for hypothesis testing and comparison of the two counties' outcomes (Figure 7-8).

Additional analysis was done to determine if the density of the wildfire smoke plume (low/medium/high) experienced during the Kincade Fire had an effect on the ER visit rate in only Sonoma County. It was determined that a generalized estimating equation with a Poisson link would be best suited to analyze the differences in smoke level. Since analysis had to be done at a zip code level, rather than an individual person. This model involves counts, and can be offset based on unique clusters. Additionally, it does not have the built in assumption that the outcomes are unrelated, and looks at how increasing the dependent variable (smoke plume density) by a level impacts the independent variable (ER visits for a specific disease group). It returned a coefficient of the estimate that was exponentiated to find the rate ratio of the incidence of ER visits between the comparison group and the reference group. P values and 95% confidence intervals were also calculated for hypothesis testing (Figure 9).

All analyses were conducted in the statistical analysis software package R Studio version 4.1.0.

HUMAN SUBJECTS AND ETHICS STATEMENT

The health outcome data was obtained via special request from the Sonoma County's District Attorney's Office for a related legal case. Although the OSHPD/HCAI emergency room dataset is considered de-identified, formal institutional review board approval has been requested and pending. As such, the results of this study remain embargoed and confidential only for viewing by the study team members and thesis evaluation committee.

RESULTS

Preliminary analysis was conducted of the numbers of ER visits by disease group and specific diseases. It shows that in Sonoma County the proportion of total emergency room visits for our composite outcome of respiratory issues increased during and after the fire, going from 16.67% of all ER visits in the 14 days prior to the fire to 21.24% of all ER visits in the 14 days during the fire, and further spiking in the 4 days after the fire to 23.23% of all ER visits (Figure 3). In terms of daily intake rates per 100,000 people this trend shows that before the fire the daily rate of ER visits for respiratory issues was 6.49 cases per 100,000 Sonoma residents. This rose to 8.34 cases per 100,000 residents during the fire and additionally to 9.05 after the fire. Among the other disease groups there was not a significant upward trend in ER visits that could be spotted just by analyzing the proportion and daily intake rates per 100,000 people.

Among the ER visits for specific diseases it was harder to find trends across the timeframe (Figure 4). There were very low numbers of ER visits for each specific disease of interest, with only 777 total visits across the timeframe. The only noticeable increases were asthma and COPD exacerbations which both increased during the fire. The proportion of asthma ER visits increased by almost 1% and the number per 100,000 cases rose by 0.5. However after the fire the proportion and number of cases per 100,000 people decreased to below pre-fire levels. The proportion of COPD cases rose by 0.3% during and after the fire and the daily number of ER visits also rose. There was a drop in ER visits for chest pain and the proportion of cases dropped almost 3% during the fire, and then after the fire rose to 1% higher than pre-fire levels.

In the control county of Shasta, the same analysis was also conducted (Figure 5). Again, the trend of a steady increase in respiratory ER visits was noticed, if not less pronounced. The rates of ER visits increased both during and after the fire. Rising from 18.4% of ER visits to 20% and then 21% following the fire. Additionally the daily case rate per 100,000 people peaked during the fire at 13.14. Among the other disease groups there were no noticeable differences during the different firetimes. Analysis of the ER visits due to specific diseases also did not identify large trends. The proportion of asthma-related ER visits slightly decreased during and after the fire. There was fluctuation among the rates of ER visits for the other specific diseases but no major changes in the proportion of visits or the daily numbers per 100,000 people.

Building off these findings, an analysis of the ER visits by disease groups in Sonoma County and the control of Shasta County was done with a logistic regression model. The results generated by this model were not found to have statistical significance, however the confidence intervals and odds ratios generated were helpful in illuminating the true effect that the firetime had on ER visits.

In Sonoma County, again the strongest trend found was the increase in the odds that a person would visit the ER for a respiratory related issue. While these time-series findings were not statistically significant, they found the odds of this occurrence in relation to before the fire increased by 19% during and 75% after the fire, when compared to before the fire (p-value 0.71 and 0.28, 95% CI 0.55-1.56 and 0.76-4.18). The only other category found to have an increase in the odds of ER visits was for psychiatric issues during the fire. Where the odds increased by 19% (p-value of 0.69, 95% CI .58-2.43).

During this time period, there were also non-statistically significant decreases in the odds of ER visits for other disease groups. The odds of being hospitalized with a cardiovascular disease during the fire decreased by 12% (p-value 0.77) and after the fire decreased by 29% (p-value of 0.46). Cerebrovascular ER visits also saw a decrease as compared to before the fire, with the odds of ER visits during the fire decreasing by 16% (p-value of 0.71) and by 43% after the fire (p-value of 0.28). Obstetrics was the final disease group to see a downward trend in ER visits, with a decrease in ER visit odds by 23% during the fire (p-value of 0.54) and 57% after the fire (p-value of 0.08).

In the control county of Shasta, there were no trends of increasing odds of ER visits over both during and after the fire. There were some increases in ER visits that were seen during the fire, but these increases diminished after the fire was over. The smallest increase was the odds of cardiovascular ER visits during the fire, which rose by 5.6% (p-value of 0.92). The next largest increase was in the odds of obstetric ER visits, where the odds increased by 58% (p-value of 0.44). The largest increase in ER visit odds was for cerebrovascular issues, which saw an increase of 129% during the fire (p-value of 0.23).

Despite these large increases in ER visits during the fire, after the fire all three of these groups saw non statistically significant decreases in the odds of ER visits. The odds of a cardiovascular ER visit decreased by 26% (p-value of 0.61) compared to pre-fire levels. Obstetric decreased by 29% (p-value of 0.622) compared to pre-fire levels. With the largest decrease coming from cerebrovascular ER visits, which saw the odds drop by 70% (p-value of 0.3).

Throughout the fire, the odds of ER visits for respiratory and psychiatric issues saw a continual decrease in Shasta County, though not statistically significant. The odds of respiratory ER visits decreased by 52% during the fire (p-value of 0.25) and the 95% confidence interval was between an 84% decrease and a 35% increase. After the fire the odds were 65% (p-value of 0.12) lower than pre-fire numbers and a 95% confidence interval was between an 89% decrease and a 4% increase. The odds of psychiatric ER visits compared to before the fire decreased by 19% during the fire (p-value of 0.71) with a 95% confidence interval of a 68% decrease and a 105% increase. After the fire the odds decreased by 56% (p-value of 0.21) with a 95% confidence interval of an 87% decrease and a 25% increase.

Further analysis was done on Sonoma County to determine the effect that smoke plume presence and density (None, Low-Medium, and High) had on the risk of ER visits for the studied disease groups (rate ratio). This model found that zip codes with low-medium smoke plume exposure were associated with a 12.6% increase in daily risk of ER visits for respiratory conditions compared to no smoke plume exposure (p-value of 0.26) and a 95% confidence interval found the range of this effect to be between a 18.6% decrease and a 38.4% increase in risk. An additional increase to a high smoke plume density was associated with a 31.1% increase in relative risk (p-value of 0.01) with a 95% confidence interval between a 8.4% decrease and a 61.1% increase, when compared to no smoke exposure. Respiratory was the only disease group that saw an increase in the relative risk of ER visits across the increasing smoke plume densities.

Cerebrovascular ER visits saw an initial decrease in relative risk by 27.5% (p-value of 0.52) when going from none to low-medium smoke plume densities, followed by a 15.7% increase in relative risk when going to a high density smoke plume (p-value of 0.75) which was not statistically significant. Obstetric ER visits also showed a not statistically significant decrease in relative risk followed by an increase, with the relative risk decreasing by 10.6% (p-value of 0.82) for low-medium density and followed by an increase in 14.6% (p-value of 0.66) for high density smoke plumes.

Additionally, it was found for psychiatric and cardiovascular ER visits that there was a decrease in the relative risk of ER visits across the increasing smoke plume densities. There was a statistically significant decrease in cardiovascular ER visits across increasing smoke plume densities, which saw a decrease in the relative risk of ER visits during low-medium density of 35.9% (p-value of 0.02), while increasing to high smoke plume density was followed by a decrease in relative risk by 38.1% (p-value of 0.002). For psychiatric ER visits, the change in relative risk was not statistically significant. For low-medium densities the relative risk of ER visits decreased by 8.5% (p-value of 0.57). High smoke plume density was associated with a 27.5% decrease in the relative risk of ER visits (p-value of 0.11).

DISCUSSION

RESPIRATORY

Before starting this analysis, it was hypothesized that there would most likely be an increase in the respiratory and cardiovascular ER visits; due to the numerous studies that have shown correlations between exposure and hospitalizations in these disease groups (Anderson et al., 2012; Lipner et al., 2019; Liu et al., 2015; Stowell et al., 2019). The preliminary analysis of just the ER visit numbers found that ER visits for respiratory diseases followed this trend in Sonoma County. During and after the fire there was a large increase in both the number and proportion of respiratory ER visits, rising from 16.67% of ER visits before the fire, to 21.24% during and 23.23% after the fire. Additionally, the number of ER visits per 100,000 people also saw a steady increase. Rising from 6.49 per 100,000 before the fire, to 8.34 per 100,000 during the fire, and 9.05 per 100,000 after the fire. Furthermore, increases in specific respiratory diseases could be identified, with asthma ER visits almost doubling in number per 100,000 people during the fire, and COPD cases also seeing an increase.

When compared to the less exposed Shasta County, it was observed that there is a much less dramatic increase in ER visits then Sonoma County. Before the fire there were 12.08 ER visits per 100,000 people in Shasta, which rose to 13.14 cases per 100,000 during the fire, and then fell to 9.47 cases per 100,000. Additionally there was a decrease in asthma related ER visits and very little change in the number of COPD cases. This preliminary data shows that there is merit to the theory that increased exposure to wildfire has an effect on respiratory ER visits, as there was a much more significant jump in the Sonoma ER visits.

This trend was further supported by the analysis with logistic regression. This analysis showed that residents of Sonoma County had an increase in the odds of respiratory disease ER visits across the firetimes, with the odds increasing by 19% (0.71) during the fire and 75% (0.28) after the fire. Conversely, Shasta County saw a decrease in the odds ratios of respiratory ER visits across the firetimes. With the odds decreasing by 51.7% (0.25) during the fire and 64.7% (0.12) after the fire. These findings did not meet the standards to be statistically significant, but do give us some key insights, suggesting that there may be a correlation between higher exposures in Sonoma County and respiratory ER visits. Additionally this demonstrates that one can observe the effects of wildfire exposure quickly after the fire begins, and continuing after the fire has ended. Furthermore, since Sonoma County saw a much larger increase in the odds of ER visits than Shasta County, it further suggests that the cause of this was likely the wildfire smoke exposure. Despite these findings, a logistic regression just comparing the different timeframes is not the best way to analyze the data. While it is important to note that our hypothesis was supported in that Sonoma seemed more impacted than the control county during and after the fire, this analysis does not help indicate why this might be the case. This time study does not account for the variation in exposure level that these counties experienced.

For this reason, it was decided that further analysis be done on Sonoma County to try and parse the impact of different levels of smoke exposure on ER visits. This analysis revealed that as the intensity of the smoke plume exposure increases (none to low-medium to high) in a zip code, there is an increase in the probability (relative risk) of ER visits for respiratory disease, with the relative risk rising 12.6% (p-value of 0.26) going from no smoke to a low-medium intensity plume, and then rising a statistically significant 31.1% (p-value of 0.01) when the smoke plume had a high intensity. This finding further demonstrates the dose response relationship between respiratory illness and wildfire smoke exposure, along with providing further evidence for why there was an increase in ER visits across the firetimes. Since the majority of the respiratory illnesses caused by particulate matter pollution are due to the particles being inhaled, consequently, the more intense a smoke plume is the more likely that a person will inhale these particles and be at risk for negative health effects.

CARDIOVASCULAR

As stated previously, it was predicted that there would be an increase in the number of cardiovascular ER visits in Sonoma County. However, the data showed the opposite trend. When analyzing the overall ER visit numbers, one can see that there was a decrease during the fire. Before the fire there were 5.77 ER visits per 100,000 people, which was the highest recorded number across the firetimes, with ER visits dropping to 4.50 ER visits per 100,000 people during the fire and 5.47 ER visits per 100,000 people after the fire. Additionally, the number of chest pain ER visits also saw a decrease during the fire. Comparatively, the numbers of ER visits in Shasta County stayed relatively stable during the fire, with the number of MI ER visits actually rising during the fire.

Logistic regression and GEE Poisson regression analysis further emphasized this trend, showing that the odds of ER visits in Sonoma County decreased by 12.5% (p-value of 0.77) during the fire and 29.2% (p-value of 0.46) after the fire, though not statistically significant. Whereas in Shasta County the odds increased by 5.6% (p-value of 0.92) during the fire and then dropped by 25.9% (p-value of 0.61) after the fire. There was also a statistically significant decrease across the different smoke plume intensities, which found that the relative risk of cardiovascular ER visits decreased by 33.9% (p-value of 0.02) when moving to low-medium smoke plume intensity and by 38.1% (p-value of 0.002) for a high intensity plume.

This data was surprising because it showed a trend that was opposite of what was expected, and what other studies had found. There are a few possible reasons for this anomaly. The ICD-10 codes that were used to identify cardiovascular disease were very broad, including people who came in with general chest pain or tightness. It is possible that after the fire started individuals with milder chest pain decided against going to the hospital, which could explain many of the trends seen in the data. The smoke exposure intensity analysis found that the heavier the plume intensity the lower the relative risk of cardiovascular ER visits, which tracks with this new possible interpretation. As these heavier plumes occured when the fire was the most severe, residents who weren't having life threatening issues would likely choose to stay home. This could also explain why for cardiovascular and chest pain ER visits, there was a decrease during the fire followed by an increase to near or exceeding pre-fire levels. With the fire extinguished, residents may have felt that it was safe to once again go to the hospital with their milder issues.

SECONDARY OUTCOMES

Cerebrovascular and obstetric had the lowest number of ER visits, with only 55 total cerebrovascular ER visits and 162 total obstetric ER visits in Sonoma County. Shasta County also saw the lowest number of ER visits in these two categories with 23 total cerebrovascular ER visits and 69 total obstetric ER visits. Due to this low statistical power it was very difficult to determine if the trends shown in the data were an accurate depiction of the true data. What the data showed was that in Sonoma County, both of these disease groups show a decrease in the odds of ER visits across the firetimes. Yet, despite the continual decrease in both cerebrovascular and obstetric ER visits across the firetimes, there was an observed increase when comparing the high smoke plume intensity to the control of no smoke plume, with the relative risk for cerebrovascular ER visits increasing by 15.7% (p-value of 0.75) and 14.6% (p-value of 0.66) for obstetric ER visits. However, none of these findings were statistically significant.

Psychiatric was another secondary disease group of interest, as there have been some studies that have linked wildfires to increased mental health issues (Ducy & Stough, 2021; Townshend et al., 2015). However, as this study could only look at psychiatric related ER visits it was unclear if this trend would arise. Again, Shasta did not offer the best dataset as a control group, with only 97 total ER visits in this category. A logistic regression analysis of this data found that there was an initial increase in the odds of psychiatric ER visits in Sonoma County during the fire, with the odds increasing by 18.7% (p-value of 0.69), however this was followed by a 32.7% (p-value of 0.38) decrease in the odds after the fire. In comparison Shasta County showed a continual decrease in the odds of psychiatric ER visits across firetimes.

However, analysis on the effect of the different smoke plume intensities on Sonoma County showed that there was an overall decrease in the relative risk of ER visits as smoke plume intensified, with a 8.5% (p-value of 0.57) decrease in relative risk going to low-medium plume intensity, followed by a 27.5% (p-value of 0.11) decrease when compared to high intensity plumes. This trend was in opposition with what was assumed would happen, and it is also important to note that the greater decrease in relative risk was associated with the highest intensity smoke plumes. It is possible that this could again be caused by residents no longer wanting to go to the hospital as the fire was at its most severe. However, without further study and additional data it is difficult to make any judgments.

Overall, the low statistical power behind these calculations and the lack of statistically significant findings makes it difficult to make any definitive interpretations. That aside, there was an overall decrease in the odds of ER visits for these disease groups across the firetimes in Sonoma County. However, there was an increase in the relative risk of ER visits in the high smoke plume for both the cerebrovascular and obstetric disease groups. These results could be interpreted as further suggestion of the association between higher levels of wildfire smoke exposure and an increase in the risk of ER visits.

LIMITATIONS

Throughout this study there were several limitations that hindered the analysis of the data. The first was the discrepancies in the ER visit numbers of Shasta County. There were many factors that made Shasta County a good candidate to be a control county for this analysis. However, after further analysis was done it was found that there were some differences between Sonoma and Shasta County characteristics. The main irregularity was that there was a much larger proportion of Shasta County residents that were hospitalized for respiratory issues. Before the fire the daily ER visits for respiratory issues in Shasta was 12.08 people per 100,000, while in Sonoma county it was 6.49 people per 100,000 residents. A possible explanation for this could be ground level ozone pollution, which was not accounted for in the exploration of the smoke plume.

According to the American Lung Association, Shasta County received an F grade for ground level ozone pollution. This was calculated by using the EPA Air Quality System. It was found that during 2017 to 2019 the annual weighted average of high ozone days was 10.3, which is significantly higher than the mark of 3.2 average days that the American Lung Association sets as a safe level (*Shasta*, n.d.). In comparison, Sonoma had a weighted average of 0.3 annual days with high ozone, and received a B grade for ozone pollution (*Sonoma*, n.d.). Exposure to ground level ozone can trigger many respiratory and cardiovascular problems, including chest pain, coughing, and throat irritation. Additionally, it can worsen asthma and reduce lung function as it inflames the lining of the lungs (*Effects of Ground Level Ozone*, n.d.). This connection between ground level ozone and respiratory and cardiovascular issues could be a reason why the initial numbers of ER visits per 100,000 people are higher in both of these categories in Shasta County.

Another limitation of this study was that our dataset was ever changing throughout the fire. Due to the magnitude of the Kincade Fire, the largest of the 2019 season and the physically largest in county history, an evacuation was ordered ("Kincade Fire Evacuation Orders," n.d.). As a result, over 186,00 people were evacuated from their homes during this time period. This posed a significant challenge for analysis as the original study pool was significantly lowered during the study period, which could have biased the results. Despite this, the overall numbers of ER visits did not change that much during the period of the fire in the time series analysis and in fact went up during the "*during"* time frame (Figure 10, 12), which suggests that evacuation did not substantially change the number of people seeking care during the fire. However, it is impossible to tell from the de-identified data if those evacuated make up a random sample of the Sonoma population. It is a possibility that the sickest patients could have been the first people to take part in this evacuation. Or conversely, that they were the ones most likely to not be able to make the evacuation. Without having an accurate way to identify who was evacuated, it is hard to tell how the analysis might have been biased.

The final limitations of this study were in the methods of statistical analysis. Although a logistic regression was used for the time series data, which is a reasonable way to analyze the data, a GEE with a Poisson link may have provided additional granularity to the time series analysis. Additionally, a different type of model like an econometric difference-in-difference model could have directly compared the outcomes in Sonoma and Shasta County.

CONCLUSIONS AND FUTURE WORK

There is clearly future work to be done exploring the effects of wildfires on public health outcomes. Further analysis would benefit by narrowing down the ICD-10 codes used to identify cardiovascular ER visits. This could be done by looking at only specific diseases or to a more narrow range of acute cardiovascular diseases. Additionally, it would be intriguing to further investigate the dose response relationship between smoke plumes and ER visits. This offered the best data during analysis, and further studies could be done to turn these observable trends into hospitalization models.

Overall, there were two major trends that can be observed from this data. The first is the continual decrease in cardiovascular ER visits during the different fire times and exposure levels. However, this can be explained by the fact that the ICD-10 codes used to identify this disease group encompassed lesser cardiovascular issues such as mild chest pain. The other significant trend was the increase in respiratory ER visits across both fire times and exposure levels in Sonoma County. This increase clearly demonstrates the dose response relationship between smoke exposure and increased respiratory ER visits. Additionally, this shows some of the danger posed by climate change. As temperatures continue to rise and the droughts continue in California, there will continue to be harsher wildfire seasons. Additionally, this analysis is only of a very limited and specific fire, and yet it is able to demonstrate the significant negative health impacts they pose. Every year in California there are thousands of fires, exposure to these fires presents a serious danger to all Californians. As wildfire seasons continue to worsen, the people of California are repeatedly placed in harm's way.

FIGURES

County	Kincade Smoke Days	Other Smoke Days	Sum of Both
Alameda County	245	207	452
Alpine County	0	24	24
Amador County	23	92	115
Butte County	27	211	238
Calaveras County	51	155	206
Colusa County	17	141	158
Contra Costa County	211	228	439
Del Norte County	4	10	14
El Dorado County	33	250	283
Fresno County	170	334	504
Glenn County	10	99	109
Humboldt County	72	56	128
Imperial County	2	77	79
Inyo County	1	26	27
Kern County	113	136	249
Kings County	21	37	58
Lake County	81	50	131

Lassen County	0	29	29
Los Angeles County	515	1338	1853
Madera County	40	89	129
Marin County	162	116	278
Mariposa County	25	66	91
Mendocino County	127	30	157
Merced County	76	106	182
Modoc County	0	32	32
Mono County	0	20	20
Monterey County	116	94	210
Napa County	58	43	101
Nevada County	14	76	90
Orange County	141	284	425
Placer County	39	266	305
Plumas County	0	74	74
Riverside County	62	127	189
Sacramento County	128	552	680
San Benito County	16	15	31
San Bernardino County	69	142	211

San Diego County	150	302	452
San Francisco County	135	150	285
San Joaquin County	129	213	342
San Luis Obispo County	63	64	127
San Mateo County	150	157	307
Santa Barbara County	86	85	171
Santa Clara County	260	232	492
Santa Cruz County	75	64	139
Shasta County	6	102	108
Sierra County	0	47	47
Siskiyou County	0	137	137
Solano County	75	98	173
Sonoma County	256	117	373
Stanislaus County	96	128	224
Sutter County	16	153	169
Tehama County	9	87	96
Trinity County	16	24	40
Tulare County	95	167	262
Tuolumne County	40	122	162

Ventura County	83	173	256
Yolo County	60	232	292
Yuba County	18	120	138

Figure 1: Number of Smoke Days by County

County	Population	Sum Kinc	Sum Other	Sum Both	# zip codes
Sonoma County	488,863	256	117	373	36
San Bernardino County	2,181,654	69	142	211	89
Riverside County	2,418,185	62	127	189	70
Shasta County	182,155	6	102	108	33
San Diego County	3,298,634	150	302	452	107
Orange County	3,186,989	141	284	425	88
Kern County	909,235	113	136	249	51
Monterey County	439,035	116	94	210	35
Los Angeles County	10,014,009	515	1338	1853	290
Tulare County	473,117	95	167	262	41
Santa Barbara County	448,229	86	85	171	23
San Joaquin County	779,233	129	213	342	44
Contra Costa County	1,165,927	211	228	439	52
Santa Clara County	1,936,259	260	232	492	58
Fresno County	1,008,654	170	334	504	55
Alameda County	1,682,353	245	207	452	49
Stanislaus County	552,878	96	128	224	24

Ventura County	843,843	83	173	256	27
Placer County	404,739	39	266	305	29
San Francisco County	873,965	135	150	285	27
San Mateo County	764,442	150	157	307	29
Solano County	453,491	75	98	173	16
Sacramento County	1,585,055	128	552	680	54

Figure 2 part 1: Demographic and Smoke information on counties over 400,000 people and Shasta County

County	**Smoke Occurrences Average Number**	**Median Age**	**% over 65**	**Foregn Born Pop**	**Median Income**	**Poverty %**
Sonoma County	10.36	43.1	19	15	87,828	6.8
San Bernardino County	2.37	33.8	11.3	21.5	67,903	13.3
Riverside County	2.70	36.2	14.1	21.3	73,260	11.3
Shasta County	3.27	41	20.2	4.9	63,091	12.6
San Diego County	4.22	36.4	13.7	22.8	83,985	10.3
Orange County	4.83	38.6	14.4	29.9	95,934	9.4
Kern County	4.88	31.9	10.7	19.8	53,067	19.1
Monterey County	6.00	35	13.2	28.6	77,514	12.7
Los Angeles County	6.39	37	13.3	33.9	72,797	13.4
Tulare County	6.39	31.4	11.2	19.7	57,692	18.8
Santa Barbara County	7.43	34.1	15	23.7	76,653	12
San Joaquin County	7.77	34.7	12.5	23	68,997	13.7

Contra Costa County	8.44	40	15.4	26.4	107,135	7.9
Santa Clara County	8.48	37.4	13.2	40.4	133,076	6.1
Fresno County	9.16	32.7	12	20.6	57,518	20.6
Alameda County	9.22	38	13.5	32.4	108,322	8.9
Stanislaus County	9.33	34.5	12.8	20	63,037	12.7
Ventura County	9.48	39	15.1	21.6	92,236	7.9
Placer County	10.52	42.4	19.1	12.9	97,723	7.1
San Francisco County	10.56	38.2	15.4	33.7	123,859	9.5
San Mateo County	10.59	39.9	15.8	35.9	138,500	6
Solano County	10.81	38.5	15.2	20.3	86,652	8.9
Sacramento County	12.59	36.6	13.7	21.1	72,017	12.6

Figure 2 cont: Demographic and Smoke information on counties over 400,000 people and Shasta County

County	**Bachelor's degree or higher**	**Largest City**	**% in largest city**	**Demographics**
Sonoma County	37.4	179,701	36.76	62.7% White, 29% Hispanic, 4.7% Asian
San Bernardino County	22.5	222,101	10.18	35.9% White, 53.7% Hispanic, 8.4% Asian
Riverside County	23.5	314,998	13.03	41.2% White, 49.7% Hispanic, 7.1% Asian
Shasta County	21.8	93,611	51.39	78.4% White, 10.8% Hispanic, 3.3% Asian
San Diego County	39.9	1,386,932	42.05	49.5% White, 33.9% Hispanic, 12.5% Asian
Orange County	41	346,824	10.88	43.4% White, 34.1% Hispanic, 22.2% Asian
Kern County	17.1	403,455	44.37	40.9% White, 54.9% Hispanic, 5.1% Asian

Monterey County	25.7	163,542	37.25	36.2% White, 60.4% Hispanic, 6.1% Asian
Los Angeles County	33.8	3,898,747	38.93	32.5% White, 48% Hispanic, 15% Asian
Tulare County	13.6	141,384	29.88	39.4% White, 65.5% Hispanic, 3.6% Asian
Santa Barbara County	34.5	109,707	24.48	50.1% White, 47% Hispanic, 5.9% Asian
San Joaquin County	20	320,804	41.17	34.3% White, 41.8% Hispanic, 17.9% Asian
Contra Costa County	43	125,410	10.76	43% White, 27% Hispanic, 18.7% Asian
Santa Clara County	53.7	1,013,240	52.33	32.3% White, 25.2% Hispanic, 39.2% Asian
Fresno County	22	542,107	53.75	37.1% White, 53.6% Hispanic, 11.2% Asian
Alameda County	50.6	440,646	26.19	31.3% White, 23.4% Hispanic, 32.4% Asian
Stanislaus County	17.3	218,464	39.51	46.4% White, 48.1% Hispanic, 6.3% Asian
Ventura County	34.8	202,063	23.95	50.8% White, 43.3% Hispanic, 7.7% Asian
Placer County	41.9	147,773	36.51	71.3% White, 15% Hispanic, 8.8% Asian
San Francisco County	59.2	873,965	100.00	41.3% White, 15.6% Hispanic, 33.9% Asian
San Mateo County	52.3	105,661	13.82	39.3% White, 25% Hispanic, 30.1% Asian
Solano County	28.9	126,090	27.80	38.8% White, 28.3% Hispanic, 16% Asian
Sacramento County	31.2	524,943	33.12	45.2% White, 23.6% Hispanic, 17.8% Asian

Figure 2 cont: Demographic and Smoke information on counties over 400,000 people and Shasta County

Firetime	Disease Group	Number	Proportion	Daily N per 100,000
before	cardiovascular	395	14.83	5.77
during	cardiovascular	308	11.46	4.50
after	cardiovascular	107	14.04	5.47
before	cerebrovascular	22	0.83	0.32
during	cerebrovascular	22	0.82	0.32
after	cerebrovascular	11	1.44	0.56
before	obstetric	76	2.85	1.11
during	obstetric	71	2.64	1.04
after	obstetric	15	1.97	0.77
before	Other	1528	57.38	22.33
during	Other	1528	56.85	22.33
after	Other	411	53.94	21.02
before	psychiatric	198	7.44	2.89
during	psychiatric	188	6.99	2.75
after	psychiatric	41	5.38	2.10
before	respiratory	444	16.67	6.49
during	respiratory	571	21.24	8.34
after	respiratory	177	23.23	9.05

Figure 3: Sonoma Hospitalization Numbers by Disease Group

Firetime	**Specific disease**	**Number**	**Proportion**	**Daily N per 100,000**
before	asthma	40	1.50	0.58
during	asthma	69	2.57	1.01
after	asthma	10	1.31	0.51
before	cardiac arrest	3	0.11	0.04
during	cardiac arrest	2	0.07	0.03
after	cardiac arrest	0	0.00	0.00
before	COPD	41	1.54	0.60
during	COPD	50	1.86	0.73
after	COPD	14	1.84	0.72
before	heart failure	7	0.26	0.10
during	heart failure	6	0.22	0.09
after	heart failure	0	0.00	0.00
before	MI	249	9.35	3.64
during	MI	179	6.66	2.62
after	MI	81	10.63	4.14
before	miscarriage	10	0.38	0.15
during	miscarriage	14	0.52	0.20
after	miscarriage	2	0.26	0.10
before	other	2313	86.86	33.80
during	other	2368	88.10	34.60
after	other	655	85.96	33.50

Figure 4: Sonoma Hospitalizations Numbers by Specific Diseases

Firetime	Disease Group	Number	Proportion	Daily N per 100,000
before	cardiovascular	203	12.10	7.96
during	cardiovascular	211	12.60	8.27
after	cardiovascular	42	12.80	5.76
before	cerebrovascular	7	0.42	0.27
during	cerebrovascular	14	0.84	0.55
after	cerebrovascular	2	0.61	0.27
before	obstetric	23	1.37	0.90
during	obstetric	40	2.39	1.57
after	obstetric	6	1.83	0.82
before	Other	1091	65.10	42.78
during	Other	1027	61.30	40.27
after	Other	203	61.90	27.86
before	psychiatric	43	2.57	1.69
during	psychiatric	48	2.87	1.88
after	psychiatric	6	1.83	0.82
before	respiratory	308	18.4	12.08
during	respiratory	335	20	13.14
after	respiratory	69	21	9.47

Figure 5: Shasta Hospitalization Numbers by Disease Group

Firetime	Specific disease	Number	Proportion	Daily N per 100,000
before	asthma	26	1.55	1.02
during	asthma	23	1.37	0.90
after	asthma	3	0.92	0.41
during	cardiac arrest	2	0.12	0.08
before	COPD	35	2.09	1.37
during	COPD	38	2.27	1.49
after	COPD	10	3.05	1.37
before	heart failure	3	0.18	0.12
during	heart failure	10	0.60	0.39
before	MI	128	7.64	5.02
during	MI	135	8.06	5.29
after	MI	24	7.32	3.29
before	miscarriage	2	0.12	0.08
during	miscarriage	8	0.48	0.31
after	miscarriage	2	0.61	0.27
before	other	1481	88.4	58.07
during	other	1459	87.1	57.21
after	other	289	88.1	39.66

Figure 6: Shasta Hospitalization Numbers by Specific Diseases

Disease Group	Firetime	Odds ratio	P Value	95% Confidence Interval
	Before	Ref	--	--
Respiratory	During	1.19	0.709	0.554, 2.56
	After	1.75	0.277	0.759, 4.18
	Before	Ref	--	--
Cardiovascular	During	0.875	0.767	0.415, 1.84
	After	0.708	0.46	0.326, 1.53
	Before	Ref	--	--
Cerebrovascular	During	0.842	0.709	0.391, 1.803
	After	0.571	0.277	0.239, 1.317
	Before	Ref	--	--
Obstetric	During	0.767	0.538	0.375, 1.558
	After	0.426	0.075	0.190, 0.927
	Before	Ref	--	--
Psychiatric	During	1.187	0.69	0.583, 2.43
	After	0.673	0.38	0.319, 1.41

Figure 7: Logistic Regression of Sonoma Hospitalizations by Disease Group compared to firetime

Disease Group	Firetime	Odds ratio	P Value	95% Confidence Interval
	Before	Ref	--	--
Respiratory	During	0.483	0.253	0.162, 1.35
	After	0.353	0.119	0.113, 1.04
	Before	Ref	--	--
Cardiovascular	During	1.056	0.92	0.422, 2.65
	After	0.741	0.61	0.278, 1.97
	Before	Ref	--	--
Cerebrovascular	During	2.286	0.225	0.768, 7.483
	After	0.3	0.299	0.0274, 1.647
	Before	Ref	--	--
Obstetric	During	1.579	0.436	0.607, 4.23
	After	0.706	0.622	0.209, 2.21
	Before	Ref	--	--
Psychiatric	During	0.81	0.71	0.318, 2.05
	After	0.424	0.21	0.129, 1.25

Figure 8: Logistic Regression of Shasta Hospitalizations by Disease Group compared to firetime

Disease Group	Smoke Plume Intensity	Relative Risk	P Value	95% Confidence Interval
	None	Ref	--	--
Respiratory	Low-Medium	1.126	0.26	0.814, 1.384
	High	1.311	.0099 **	0.916, 1.611
	None	Ref	--	--
Cardiovascular	Low-Medium	0.661	.021 *	0.704, 0.939
	High	0.619	.0024 **	0.485, 0.843
	None	Ref	--	--
Cerebrovascular	Low-Medium	0.725	0.52	0.375, 1.937
	High	1.157	0.75	0.299, 2.812
	None	Ref	--	--
Obstetric	Low-Medium	0.894	0.82	0.371, 1.244
	High	1.146	0.66	0.487, 2.103
	None	Ref	--	--
Psychiatric	Low-Medium	0.915	0.57	0.735, 1.244
	High	0.725	0.11	0.616, 1.078

Figure 9: Poisson Regression of Sonoma Hospitalizations compared to Smoke Plume Intensity

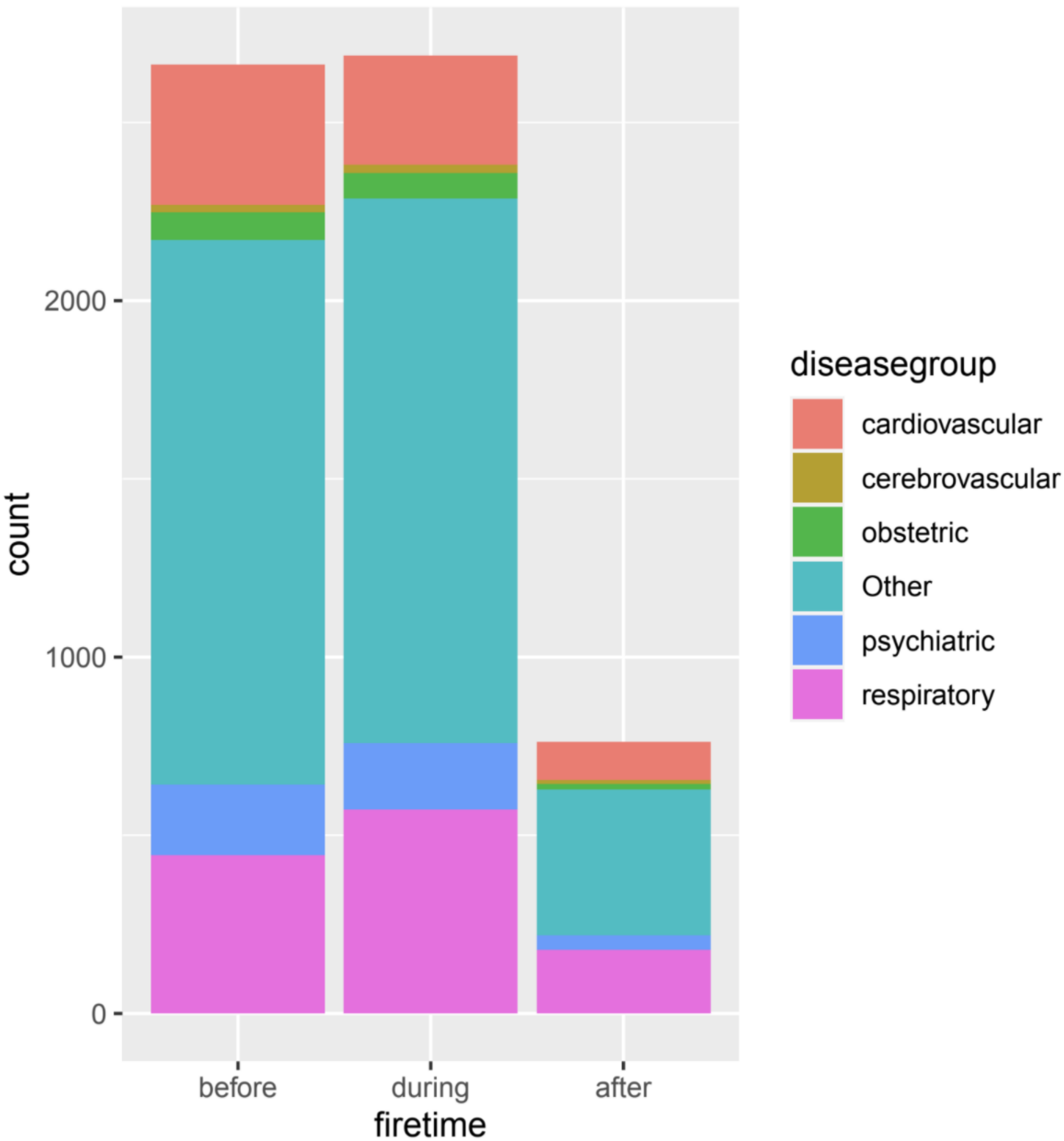

Figure 10: Graph of Sonoma Hospitalization Numbers by Disease Group

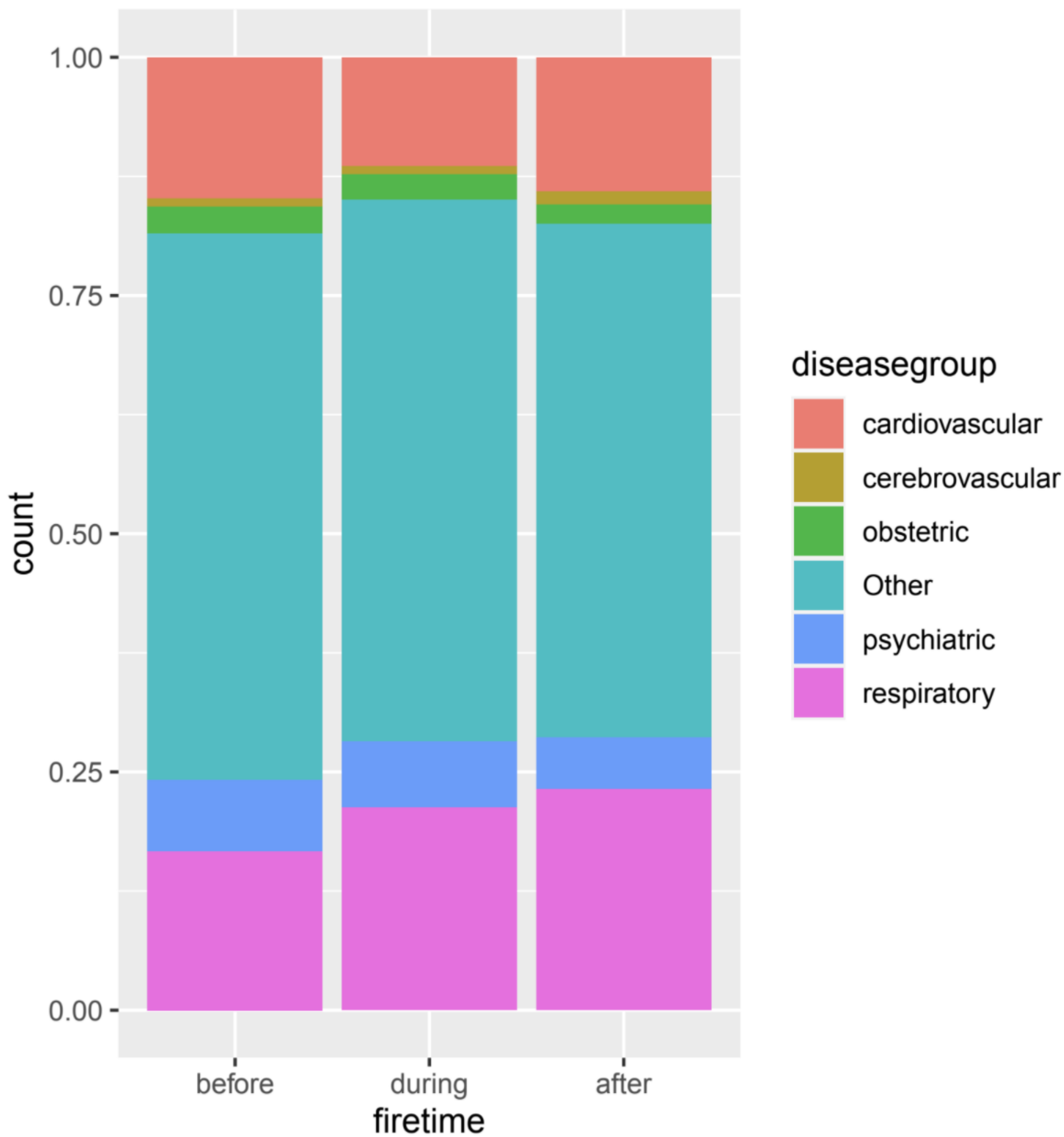

Figure 11: Filled Graph of the Proportions of Sonoma Hospitalizations by Disease Group

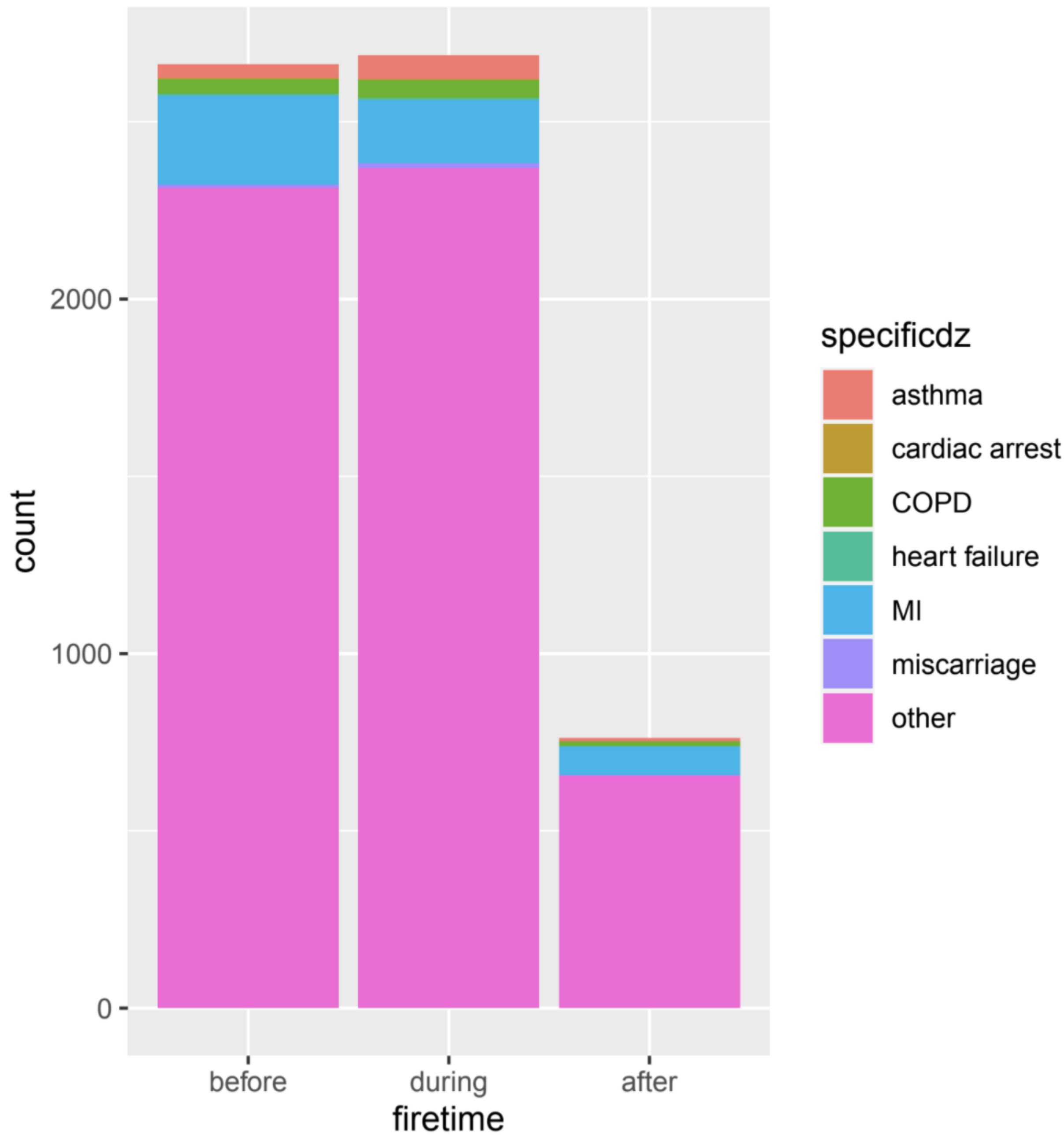

Figure 12: Graph of Sonoma Hospitalization Numbers by Specific Diseases

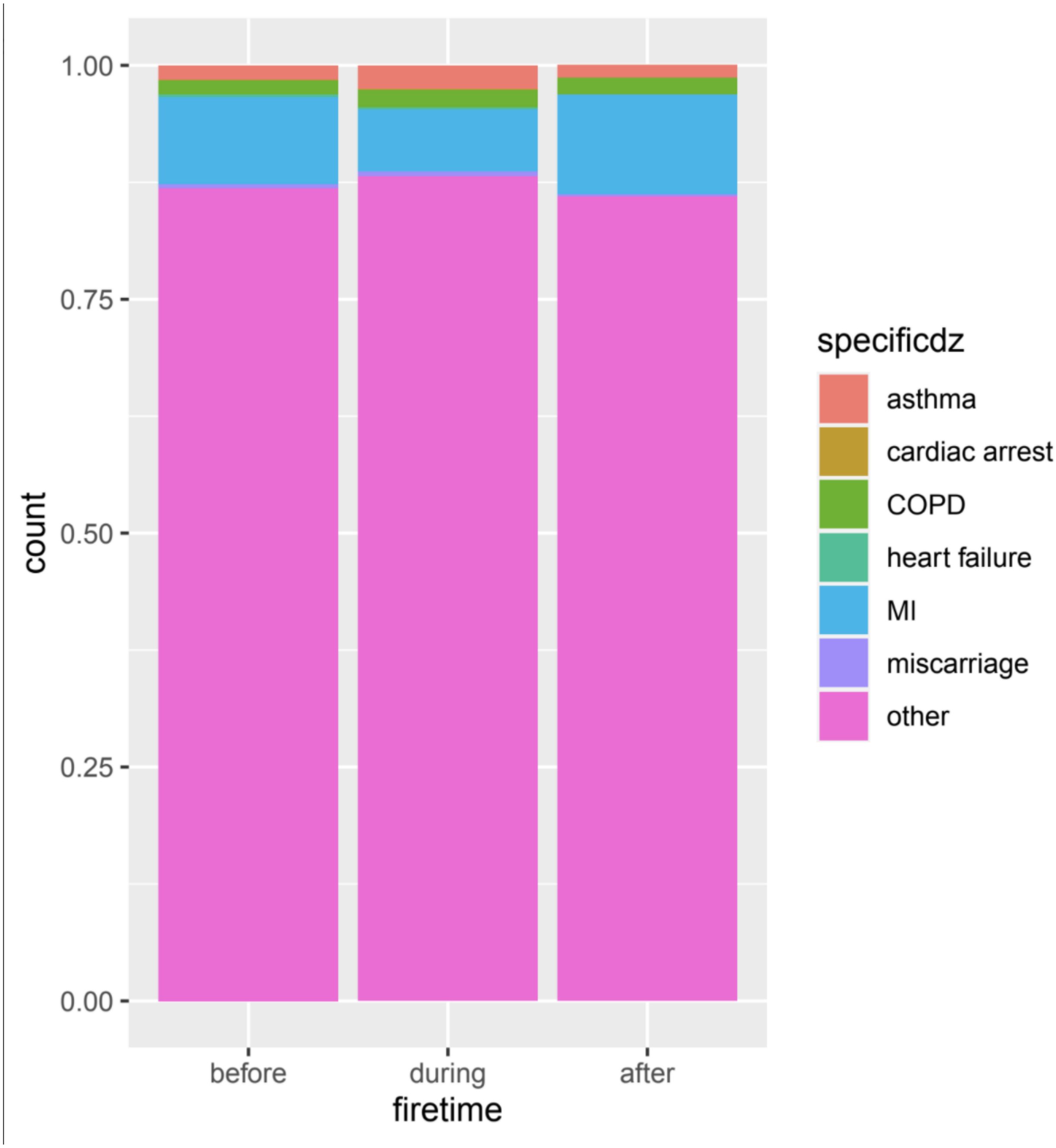

Figure 13: Filled Graph of the Proportions of Sonoma Hospitalizations by Specific Diseases

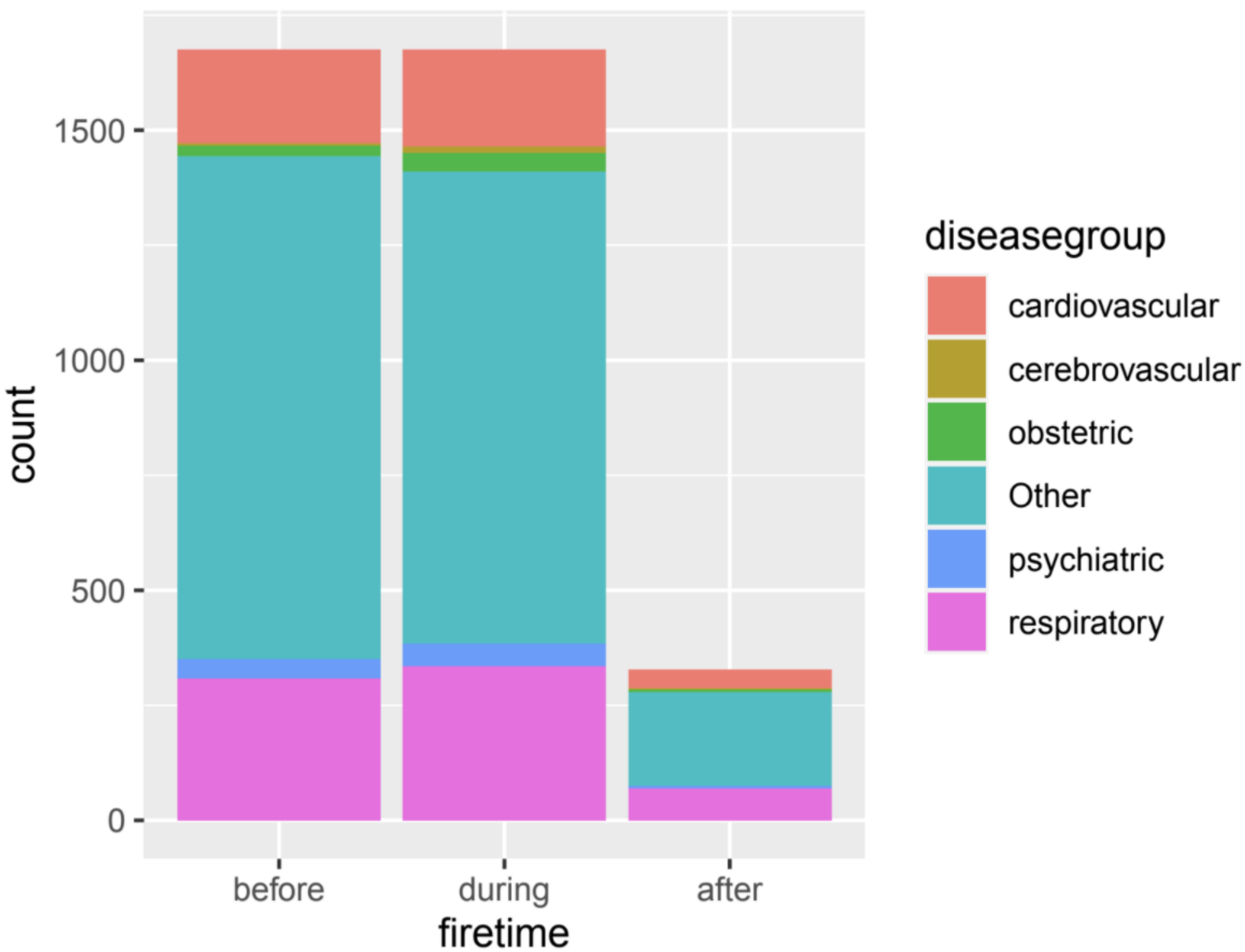

Figure 14: Graph of Shasta Hospitalization Numbers by Disease Group

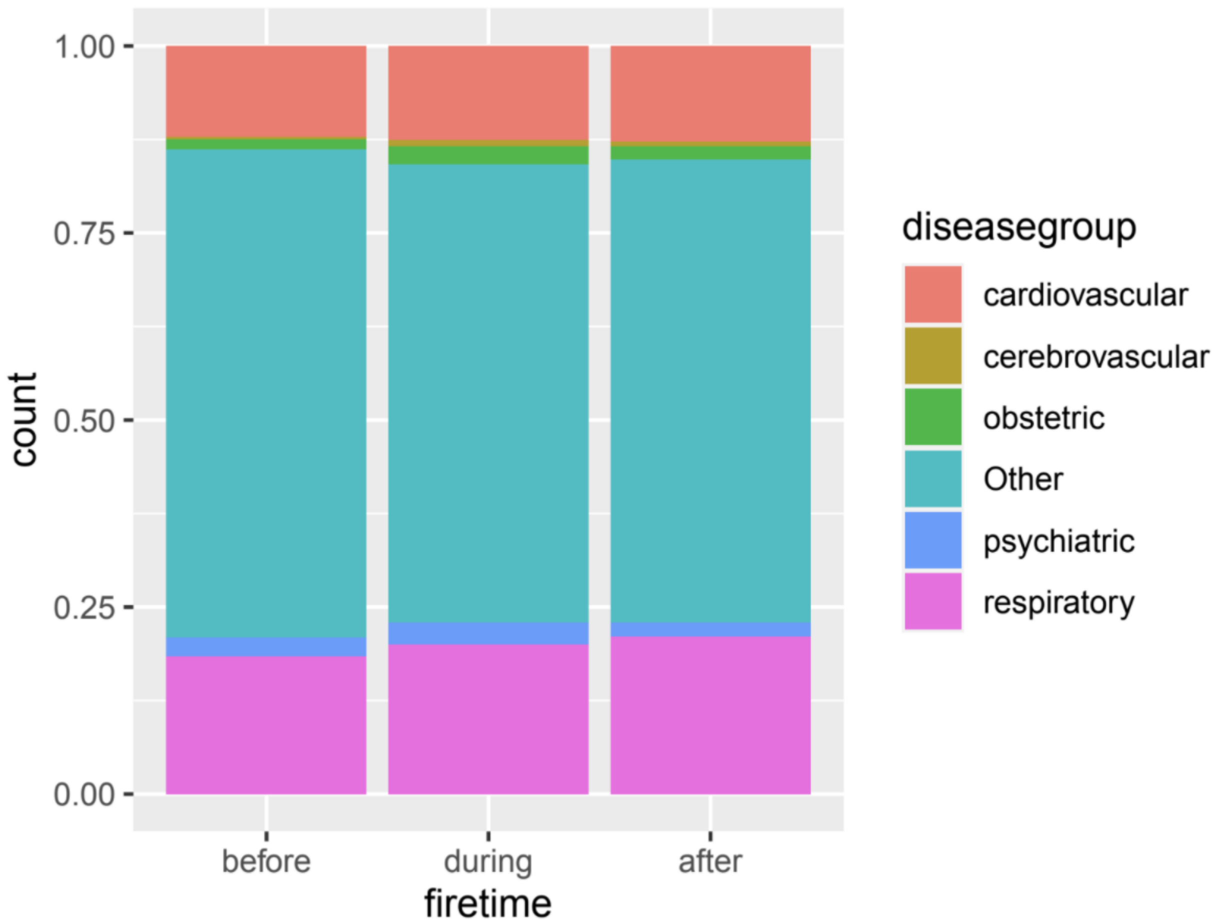

Figure 15: Filled Graph of the Proportions of Shasta Hospitalizations by Disease Group

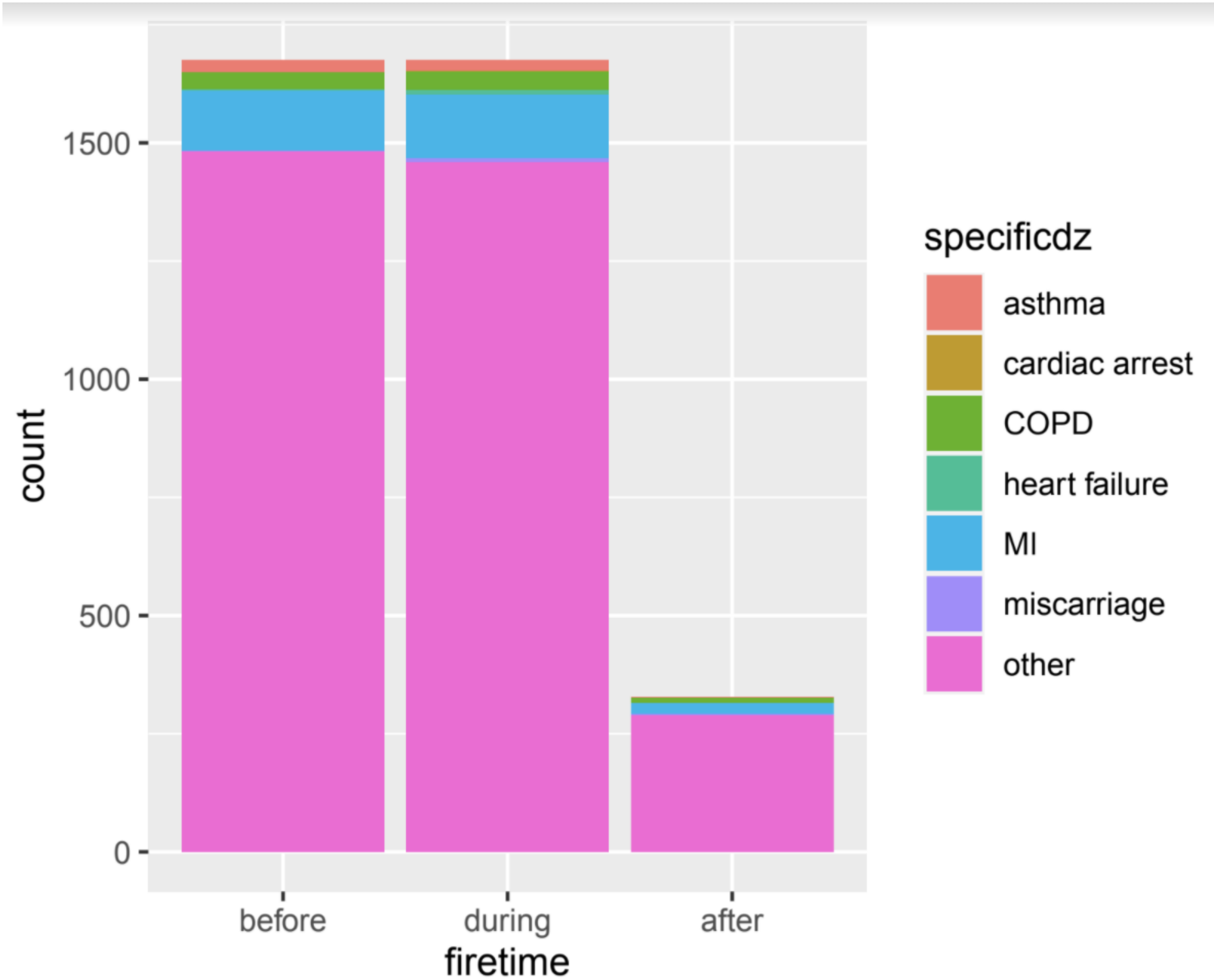

Figure 16: Graph of Shasta Hospitalization Numbers by Specific Diseases

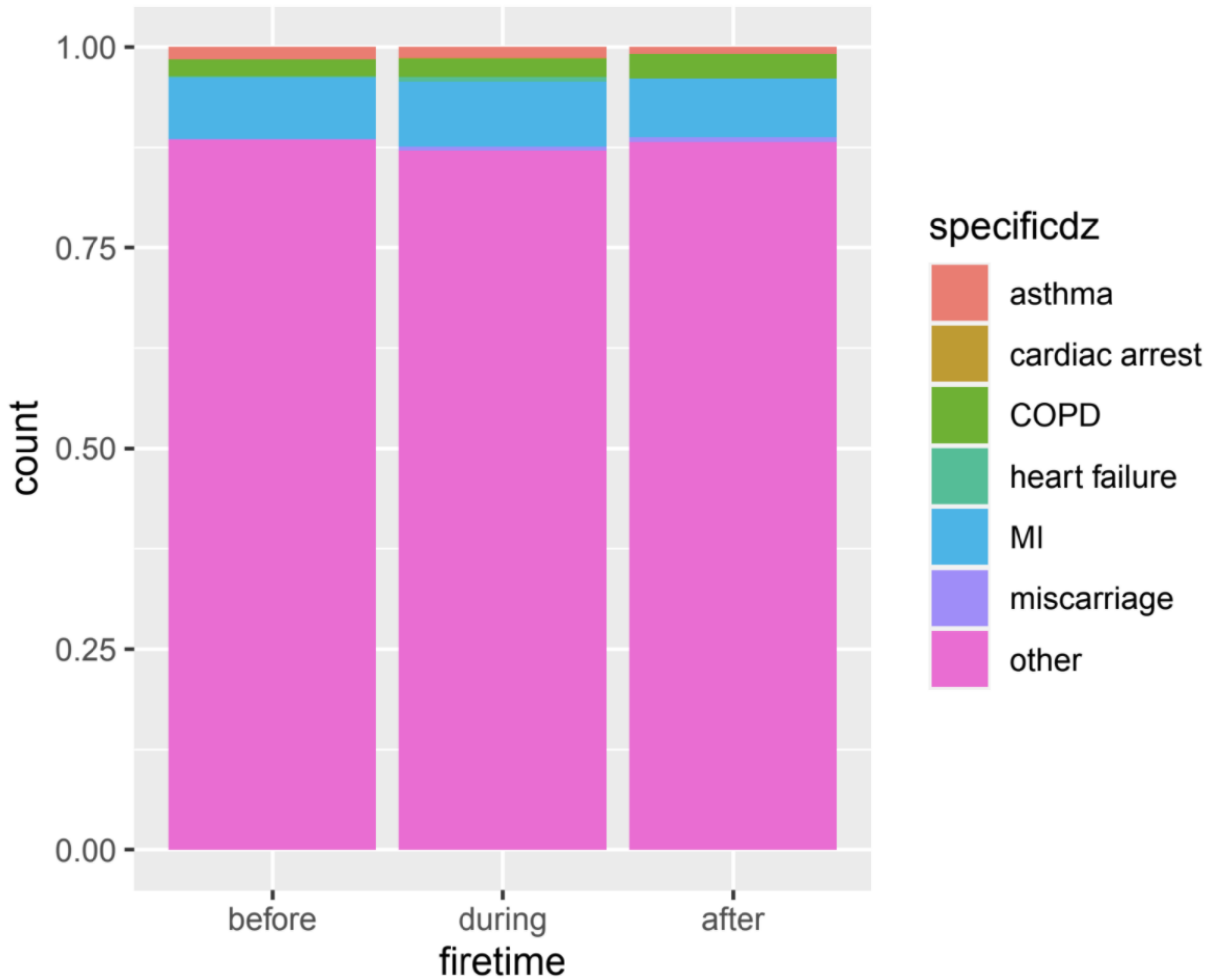

Figure 17: Filled Graph of the Proportions of Shasta Hospitalizations by Specific Diseases

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