The Impact of Seasonal Temperature Variation on Opioid Overdose Deaths:

A Comprehensive Analysis

Abstract

BACKGROUND: The opioid epidemic is a major issue in the United States, particularly since 2013 with the rise in synthetic opioids. While there has been many past studies conducted to investigate the relationships between demographic and socioeconomic groups with overdoses, there has been little work done investigating temperature. The few studies that have looked at temperature have found evidence suggesting that colder months have higher rates of overdose deaths than warmer months.

OBJECTIVE: To investigate the relationship between temperature and risk of opiate-related deaths

METHODS: Using HCUP's 2016 NEDS data, ~221,000 opiate-related emergency department visits were identified after filtering for adults with known admission month and death status. With this data, logistic regression models were used with the outcome variable representing death status and predictor variables being age group, admission month, sex, patient zip code median income quartile, patient location, and hospital region. By using logistic regression models, odds ratios and their corresponding 95% confidence intervals could be found to represent risk of death during an emergency department visit.

RESULTS: Only the month of September had a statistically significant 95% confidence interval where the interval did not cross 1. The months with the highest odds ratios were February, March, and April and the months with the lowest odds ratios were June, August and September. For the other predictor variables, odds of death increased with age group, being male, and for hospitals in the west region.

CONCLUSION: Opiate-related overdose risk of death was investigated by using logistic regression models on patient death status with a focus on odds ratios and their corresponding 95% confidence intervals. It was found that the risk of death from an opiate-related overdose was generally higher during colder months and lower during warmer months. Additionally, risk of death increases with age group and males and decreases in the west region.

Introduction

While the Centers for Disease Control and Prevention defines the opioid epidemic in the United States as consisting of three waves, most people think about the third wave when discussing the issue. The third wave began in 2013 when synthetic opioid deaths began to increase rapidly, becoming the leading cause of death among opioid groups. Given that drug overdoses including fentanyl, a synthetic opioid, is the leading cause of death among people between the ages of 18 and 45 in the United States, there have been numerous studies done on opioid related overdoses.

Most studies in the past have focused on relationships between overdoses and demographic information, such as sex, race, and income. These study findings are useful in that at-risk communities may be able to be identified and have policies or programs implemented in an attempt to reduce future drug related overdoses. However, there is a dearth of studies on seasonal variation in opioid-related deaths and their relationship with temperature. Some studies have concluded that there is a relationship between temperature and overdoses, finding results suggesting that 'low average temperatures ... were associated with higher odds of fatal opioid overdose' [1], meaning that colder months may have higher rates of overdose deaths.

There are various theories behind why overdose rates tend to increase with lower temperatures, mostly revolving around human biology and behavior. Biologically, opioids impact the body's ability to regulate body temperature along with making breathing more difficult.

These factors increase risk of death as the heart, nervous system, and other organs are not able to function normally. Additionally, seasonal affective disorder is more prevalent in the winter, causing people to feel more sad, depressed, and anxious [2]. These feelings may make people more inclined to find something to change the way that they feel and turn to opioids. Pair that

with people being more isolated and less social when it is cold and the chances increase of someone having an overdose without anybody quickly noticing and getting help. Another factor to consider is that winter weather may change drug trafficking patterns, which may increase the risk of an user accidentally consuming drugs that are laced with opiates [1]. The winter weather may also impact emergency response and transit times, increasing the chances of death in the event of an overdose.

As such, being able to predict overdose deaths by month can be essential in resource planning for hospitals and emergency services to help them allocate assets based on time of year. Location is something that greatly influences temperature along with the calendar month, as northern areas in the United States tend to have colder winters, and temperatures in general, than southern areas. Because of this, location needs to be accounted for along with month to get a more holistic idea as to how temperature impacts opioid related deaths.

In order to investigate this, data provided by the Healthcare Cost and Utilization Project (HCUP) will be used, specifically the National Emergency Department Sample (NEDS) data from 2016. This enables the use of a regression model to predict if a patient admitted to the emergency department due to an opioid related overdose will die during their hospitalization or not. With this model, variable coefficients for each month can be found, which would help determine whether or not colder temperatures increase the risk of opioid related overdose mortality. Given all this, we believe that there is an association between the likelihood of an opioid related overdose emergency department hospitalizations resulting in death and months that tend to have colder temperatures. The null hypothesis is that there is no relationship between month of admission and the likelihood of an opioid related overdose emergency department hospitalizations resulting in death.

Methods

The goal of this study is to investigate the relationship between temperature and risk of opioid related drug overdose deaths in emergency departments of the United States. To study this, analysis will be focused on the relationship between calendar month and death risk, as certain months are colder and warmer than others. The HCUP NEDS dataset from 2016 will be used as it contains nationally representative emergency department data, allowing for diverse geography of hospitals and patients. While it would be ideal to have the latest NEDS dataset version, 2016 is the most recent version available for use. This should not impact the study results too much though, as the national trend of increasing opioid related deaths had already begun in 2016.

The study population will include cases where the patient's age at admission declares them as an adult, so at least 18 years old. After that, the data has to be subsetted to ensure that important variables to this study's values are known, with these being month of admission and death outcome. Lastly, the ICD-10 diagnosis codes need to be checked to see if one of the first five diagnoses are opioid related. The codes that were used to identify this was referenced from the Agency for Healthcare Research and Quality [3]. Table 4 containing ICD-10 codes was used, with the specific sections being 'Opioid abuse/dependence', 'Opioid use', 'Poisoning', and 'Adverse events'.

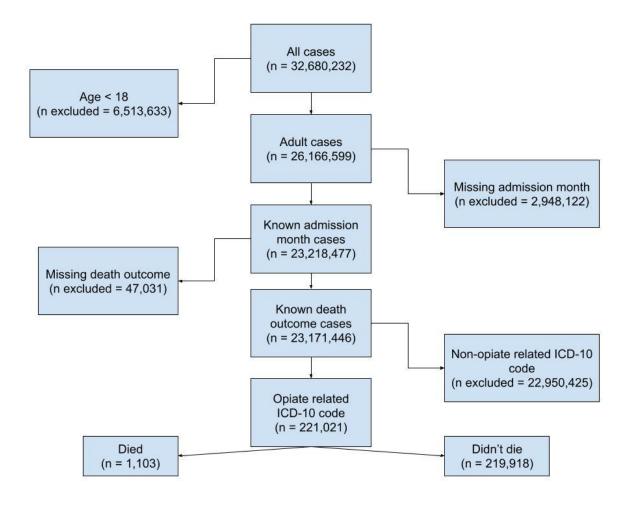


Figure 1: Inclusion/Exclusion Flowchart

There are a number of independent variables that will be included in model specification, with the most important being admission month. Admission month specifies the month that the patient was admitted to the emergency department and given that this study is focusing on the calendar month as a way to get a general idea of temperature, this information is essential. The other independent variables that will be utilized are age at admission, sex, patient county urban/rural code, patient zip code median household income quartile, and hospital region. Each of these variables except for hospital region are important to consider as they are all known to

contribute to opioid overdose risk and all of these independent variables will be treated as categorical. Hospital region is important to include as well because geographic region influences temperature, which coincides with the hypothesis that more deaths occur in months of colder temperature. Each month will be its own category. Age at admission is grouped into groups of 18-29, 30-39, 40-49, 50-59, and 60+. Sex is classified as being male, female, and missing. Zip code median income quartiles are broken down into less than \$43,000, \$43,000 to \$53,999, \$54,000 to \$70,999, greater than \$71,000, and missing. Patient county location is classified as central counties of metro areas with a population of 1 million or more, fringe counties of metro areas with a population of 1 million or more, counties of metro areas with a population between 250 thousand and 1 million, counties of metro areas with a population less than 250 thousand, micropolitan counties, non-metro or micropolitan counties, and missing. Hospital region is broken down into northeast, midwest, south and west. The baseline reference categories that will be used will be 18-29 for age, January for month, male for sex, less than \$43,000 for zip code median income quartile, central counties of metro areas with population greater than 1 million for patient county location, and northeast for hospital region.

The outcome variable of interest will be death status, defining whether or not the patient died during their visit. In NEDS, this variable is divided into three categories: did not die, died in the emergency department, and died in hospital. For the purposes of this study, this variable will be converted to have binary values of whether or not the patient died.

For data analysis, the SAS LOGISTIC procedure will be utilized to create a logistic regression model to predict whether or not the patient died. Additionally, stratified logistic regression models by hospital region will be used to account for regional weather impact. These models will include the same independent variables as the main model with hospital region being

excluded. With these logistic regression models, parameter odds ratio estimates and confidence intervals will be able to be found, which will be particularly important to see the effect of individual months. The odds ratios will demonstrate which groups have higher or lower odds of dying during their opioid-related emergency department visit relative to the reference group.

Results

After subsetting the data, the following subject breakdown for each independent variable by death status was found.

	Did Not Die (n = 219,918)	Did Die (n = 1,103) n (column %)	
Variable	n (column %)		
Age Group			
18 - 29	61,743 (28.08)	241 (21.85)	
30 - 39	55,275 (25.13)	276 (25.02)	
40 - 49	36,233 (16.48)	179 (16.23)	
50 - 59	35,806 (16.28)	185 (16.77)	
60+	30,861 (14.03)	222 (20.13)	
Month			
January	17,283 (7.86)	94 (8.52)	
February	16,312 (7.42)	104 (9.43)	
March	18,425 (8.38)	103 (9.34)	
April	17,871 (8.13)	105 (9.52)	

May	19,032 (8.65)	88 (7.98)
June	18,740 (8.52)	82 (7.43)
July	19,761 (8.99)	92 (8.34)
August	19,589 (8.91)	84 (7.62)
September	19,364 (8.81)	76 (6.89)
October	18,375 (8.36)	93 (8.43)
November	17,507 (7.96)	88 (7.98)
December	17,659 (8.03)	94 (8.52)
Sex		
Male	121,918 (55.44)	665 (60.29)
Female	97,950 (44.54)	438 (39.71)
Missing	50 (0.02)	0 (0.00)
Zip Code Median Income Qu	artile	
< \$43,000	70,021 (31.84)	370 (33.54)
\$43,000 - \$53,999	53,427 (24.29)	241 (21.85)
\$54,000 - \$70,999	48,734 (22.16)	240 (21.76)
\$71,000+	42,531 (19.34)	229 (20.76)
Missing	5,205 (2.37)	23 (2.09)
Patient Location		
Central Counties of Metro Areas (Population >= 1m)	71,582 (32.55)	355 (32.18)
Fringe Counties of Metro Areas (Population >= 1m)	55,580 (25.27)	303 (27.47)
Counties of Metro Areas	43,218 (19.65)	214 (19.40)
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(250k <= Population < 1m)		
Counties of Metro Areas (50k <= Population < 250k)	18,571 (8.44)	91 (8.25)
Micropolitan Counties	18,943 (8.61)	89 (8.07)
Non Metro or Micropolitan Counties	>9,800	>40
Missing	>2,200	<11
Hospital Region		
Northeast	50,863 (23.13)	278 (25.20)
Midwest	63,933 (29.07)	357 (32.37)
South	55,012 (25.01)	288 (26.11)
West	50,110 (22.79)	180 (16.32)

Table 1: Population Breakdown by Variable

From table 1, it can be seen that the number of emergency department visits decreased with each increase in age group. Similarly, visits decreased with each quartile increase in patient zip code median income. There are also significantly more visits for males than females, as well as decreasing visit amounts as patient location population becomes smaller. The amount of visits by region were relatively similar for the most part except for hospitals from the midwest, where there were many more visits than in the other regions.

From the logistic regression models run, odds ratios and their corresponding 95% confidence intervals were able to be found.

	Unadjusted Odds Ratio	Adjusted Odds Ratio
Variable (Reference Group)	OR (95% CI)	OR (95% CI)
Age Group (Reference = 18 -	29)	
30 - 39	1.279 (1.076, 1.521)	1.280 (1.076, 1.522)
40 - 49	1.266 (1.043, 1.536)	1.276 (1.050, 1.551)
50 - 59	1.324 (1.092, 1.604)	1.360 (1.120, 1.650)
60+	1.843 (1.535, 2.213)	2.021 (1.679, 2.432)
Month (January)		
February	1.173 (0.887, 1.551)	1.170 (0.884, 1.548)
March	1.028 (0.777, 1.360)	1.024 (0.774, 1.356)
April	1.080 (0.817, 1.428)	1.072 (0.811, 1.418)
May	0.850 (0.635, 1.138)	0.847 (0.633, 1.134)
June	0.805 (0.598, 1.083)	0.801 (0.595, 1.078)
July	0.856 (0.642, 1.142)	0.849 (0.636, 1.132)
August	0.788 (0.587, 1.059)	0.783 (0.583, 1.052)
September	0.722 (0.533, 0.977)	0.716 (0.528, 0.969)
October	0.931 (0.698, 1.240)	0.926 (0.695, 1.235)
November	0.924 (0.691, 1.237)	0.919 (0.686, 1.230)
December	0.979 (0.735, 1.304)	0.970 (0.728, 1.292)
Sex (Male)		
Female	0.820 (0.726, 0.925)	0.811 (0.718, 0.916)
Missing	-	-
Zip Code Median Income Quartile (< \$43,000)		

\$43,000 - \$53,999	0.854 (0.726, 1.004)	0.890 (0.753, 1.051)	
\$54,000 - \$70,999	0.932 (0.792, 1.097)	0.956 (0.806, 1.134)	
\$71,000+	1.019 (0.864, 1.202)	1.048 (0.870, 1.261)	
Missing	0.836 (0.548, 1.275)	1.176 (0.721, 1.918)	
Patient Location (Central Co	unties of Metro Areas [Populat	ion >= 1m])	
Fringe Counties of Metro Areas (Population >= 1m)	1.099 (0.943, 1.282)	1.037 (0.875, 1.229)	
Counties of Metro Areas (250k <= Population < 1m)	0.998 (0.842, 1.184)	1.040 (0.876, 1.235)	
Counties of Metro Areas (50k <= Population < 250k)	0.988 (0.784, 1.245)	1.004 (0.794, 1.269)	
Micropolitan Counties	0.947 (0.751, 1.196)	0.962 (0.758, 1.220)	
Non-Metro or Micropolitan Counties	0.925 (0.678, 1.262)	0.879 (0.641, 1.205)	
Missing	0.546 (0.243, 1.225)	0.579 (0.226, 1.481)	
Hospital Region (Northeast)			
Midwest	0.979 (0.836, 1.145)	1.004 (0.855, 1.180)	
South	0.938 (0.802, 1.095)	0.948 (0.806, 1.114)	
West	0.643 (0.538, 0.770)	0.619 (0.512, 0.748)	

Table 2: Odds Ratios for Variables

The primary variable of interest is month of admission, where January was set as the reference category. Only one month, September, had a confidence interval that did not cross 1, with the estimate and interval being 0.716 (0.528, 0.969). The months with point estimate odds

ratios greater than 1 are February, March, and April and the months with point estimate odds ratios slightly below 1 are October, November, and December. However, all the months' point estimate odds ratios (besides September) were not statistically significant as their corresponding 95% confidence intervals crossed 1. Warmer months from May through September have noticeably lower odds ratios than the other months, particularly August and September. For age group, the odds ratios increased overall as age group did, especially for the 60+ age group who had twice the odds of dying compared to someone in the 18-29 age group. Females have much lower odds of dying compared to males, with their odds ratio and confidence interval being 0.811 (0.718, 0.916). For the median income quartile of a patient's zip code, those in the quartiles of \$43,000 to \$53,999 and \$54,000 to \$70,999 had lower odds of dying than those in zip codes with a median income that is less than \$43,000. Those in areas with a median income greater than \$71,000 had slightly higher odds of dying relative to those where the median income is less than \$43,000. For patient location, the baseline category was central counties of metro areas with a population greater than 1 million. All the other metro area counties had odds ratios greater than 1 and had higher odds of dying while micropolitan and non-metro or micropolitan counties had a lower likelihood of dying. The odds of dying based on the hospital region were all pretty similar with the exception of the west region, where the odds of dying were much lower with an odds ratio of 0.619 and a confidence interval of (0.512, 0.748).

Since month is the primary variable of interest and temperature varies by area/region, the odds ratios by month were also looked at for each region.

Reference - January	Full	Northeast	Midwest
February	1.170 (0.884, 1.548)	1.251 (0.775, 2.020)	1.970 (1.027, 3,780)
March	1.024 (0.774, 1.356)	0.909 (0.549, 1.504)	1.969 (1.042, 3.720)
April	1.072 (0.811, 1.418)	1.201 (0.748, 1.929)	1.390 (0.701, 2.757)
May	0.847 (0.633, 1.134)	0.733 (0.430, 1.251)	1.845 (0.977, 3.486)
June	0.801 (0.595, 1.078)	1.084 (0.670, 1.755)	0.814 (0.382, 1.734)
July	0.849 (0.636, 1.132)	0.826 (0.497, 1.373)	1.335 (0.686, 2.600)
August	0.783 (0.583, 1.052)	0.791 (0.472, 1.328)	0.974 (0.479, 1.979)
September	0.716 (0.528, 0.969)	0.665 (0.385, 1.150)	1.133 (0.571, 2.246)
October	0.926 (0.695, 1.235)	0.850 (0.506, 1.426)	1.692 (0.885, 3.232)
November	0.919 (0.686, 1.230)	0.806 (0.472, 1.376)	1.631 (0.850, 3.130)
December	0.970 (0.728, 1.292)	1.044 (0.633, 1.720)	2.034 (1.083, 3.818)

Reference - January	Full	South	West
February	1.170 (0.884, 1.548)	0.835 (0.476, 1.462)	0.966 (0.518, 1.802)
March	1.024 (0.774, 1.356)	1.010 (0.602, 1.693)	0.586 (0.293, 1.172)
April	1.072 (0.811, 1.418)	1.137 (0.688, 1.879)	0.569 (0.279, 1.158)
May	0.847 (0.633, 1.134)	0.589 (0.328, 1.057)	0.695 (0.358, 1.352)
June	0.801 (0.595, 1.078)	0.521 (0.281, 0.965)	0.792 (0.417, 1.504)
July	0.849 (0.636, 1.132)	0.735 (0.425, 1.271)	0.724 (0.377, 1.391)
August	0.783 (0.583, 1.052)	0.893 (0.530, 1.505)	0.498 (0.240, 1.036)
September	0.716 (0.528, 0.969)	0.539 (0.295, 0.987)	0.753 (0.397, 1.431)
October	0.926 (0.695, 1.235)	0.891 (0.524, 1.515)	0.553 (0.272, 1.127)
November	0.919 (0.686, 1.230)	0.868 (0.502, 1.500)	0.671 (0.340, 1.321)

December	0.970 (0.728, 1.292)	0.616 (0.340, 1.116)	0.617 (0.308, 1.235)
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Table 3: Odds Ratios for Variables by Hospital Region

For the northeast region, nothing can really be seen as odds ratios switched off being greater and less than 1. In the midwest though, the majority of months (9) had odds ratios greater than 1. Some of these ratios were close, if not greater than 2, with these months being February, March, May, and December. For February, March, and December in particular, their confidence intervals were fully above 1. In the south, most odds ratios were below 1, with May, June, and September being particularly low and being between 0.5 and 0.6. The west region had all months with odds ratios less than 1, with none of them being close to 1 except for February.

Discussion

Overall, concrete conclusions using months' odds ratios and 95% confidence intervals are not able to be made given that nearly all the intervals crossed one. The months with the highest point estimate odds ratio values were those at the end of winter, being February, March, and April. The months with the lowest point estimate odds ratios were those that occurred in the summer and fall, with them being the months from May through September. This general trend of lower odds of opioid related overdose deaths in warmer months corresponds with past findings that there is higher risk of overdose deaths during times with colder temperature.

Due to the intriguing nature of the monthly odds ratios for the midwest and west region, some simple post-hoc analysis was performed to quickly look at the breakdown of death status

and total emergency department visits for the midwest and west regions by month. The midwest region demonstrated how emergency department visits increased during warmer months and decreased in colder months. The west region exhibited a similar pattern but to less of an extent.

Midwest Region	Did Not Die	Did Die	Total ED Visits	
Month	Month			
January	3,763	14	3,777	
February	3,565	26	3,591	
March	4,138	30	4,168	
April	3,881	20	3,901	
May	4,371	30	4,401	
June	4,321	13	4,334	
July	4,620	23	4,643	
August	4,694	17	4,711	
September	4,713	20	4,733	
October	4,310	27	4,337	
November	4,245	26	4,271	
December	4,242	32	4,274	

Table 4: Emergency Department Breakdown for Midwest Region

There are some other key results that can be determined through the variable odds ratio values that also agree with past literature. These are that the risk of dying increased as age group increased, if someone was male, and if someone was from a metropolitan area. One result that

does not agree with literature is the median income quartile of a patient's zip code, where the only group with a higher risk of death than the less than \$43,000 group is the greater than \$71,000 group. However, this is likely due to unreported and untreated cases of opioid overdoses within lower socioeconomic groups.

The strength of this study revolves around the use of the NEDS data provided by HCUP. This dataset has a national scope, which enables analysis across diverse geographic regions which is essential when studying the impact of temperature variation. Regional analysis indicated that hospitals in the Midwest and Northeast regions had higher overdose death rates in winter months compared to the South and West. Moreover, because NEDS is comprehensive and nationally representative, the death rates and odds ratios that are found are theoretically representative of the entire country. Lastly, NEDS is a very large dataset, so the final dataset was still substantial (~221,000 observations) even after subsetting the data.

While using NEDS data has its strengths, there are many limitations as well that are important to take into consideration with the first being that the data used in this study is from 2016. The third wave opioid epidemic began in 2013 when synthetic opioid related deaths began to significantly rise. Since then, the opioid crisis has changed in many ways including patterns and policy. Another limitation with NEDS revolves around available variables and using month as a proxy variable for temperature. The available variables in the dataset are missing many covariates that influence opioid overdose rates, including race, ethnicity, and marital status. Similarly, the admission month variable was used as a proxy variable to get a general idea of temperature. Because this is effectively looking at average temperature of each month, analysis is susceptible to missing extreme weather events. Furthermore, it is unknown how hospitals are grouped into the region variable, which is important as geographic location has an influence on

monthly temperatures. Another potential weakness is that NEDS relies on administrative data, which may be susceptible to having underreported or misclassified cases. A final weakness is that NEDS only accounts for emergency department visits. This means that patients who experience an overdose must stay alive long enough to be admitted to the emergency department and have the visit be documented. Because of this, more severe overdose instances are likely not included in this data because the patients have a higher likelihood of dying before making it to the hospital.

In comparison to earlier studies, this research study provides a more nuanced view of how environmental factors like temperature, coupled with some demographic and socioeconomic variables, can impact the risk of opioid overdose deaths. The regional analysis particularly underscores the varying impact of temperature across different parts of the country, which is a unique perspective to opioid epidemic research.

Conclusion

From the 2016 NEDS dataset provided by HCUP, opioid related overdose risk of death was able to be investigated. By running logistic regression models on patient death status, odds ratios and their corresponding 95% confidence intervals were able to be found for each independent variable included. With these ratios, it was found that the risk of death from an opiate-related overdose was higher in months that are typically colder and lower in months that are typically warmer. Additionally, risk of death increases as age group increases, if a patient is male, or if a patient is from a metropolitan area. The odds ratio for hospitals in the west region is also much lower than that of the other three regions. For patient zip code median income

quartile, the highest quartile of median income had the highest	odds ratio followed by the lowest
quartile.	

Hypothetical Tweets

- New study finds evidence that opioid related overdose death risk is increased in colder months. The months with highest risk are January, February, and April while the months with the lowest risk are June, August, and September.
- 2) Researchers find that the western region of the United States has a significantly lower risk of dying from an opioid related overdose in an emergency department setting relative to the northeast, midwest, and southern regions.

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