Analysis of Opioid Crisis in the U.S

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ABSTRACT The unnatural fatal overdoses of opioids have increased over the past decade resulting in many more deaths in the United States. As lawmakers attempt to create policies in response, they need data driven analysis of trends at a county level. Over time, policies controling prescription opioids have led to an increase in non-prescription opioid use. This paper explores the reponse, by county, of health region, county, and police division, to opioid fatalities falling with the categories of fentanyl, heroin, prescription opioids and other opioids.

INDEX TERMS: Addiction, Crime, Crisis, Department of Health, Emergency, Forensic Epidemiology**,** Fatality, Hospitals, Opioid, United States of America (USA), and Virginia State.

I. INTRODUCTION

The unnatural fatal overdoses of opioids have increased, particularly over the past decade. Some recent studies found that increases in county unemployment rates predict increases in opioid death rates and that macroeconomic shocks drive the overall drug death rate [4][6]. Also, the CDC issued a report stating that "Medicaid recipients and other low-income populations are at high risk for prescription drug overdose. [5]

We decided to select Virginia as a case study due to the increasing population, its diverse distribution, and demographics. In recent years, many companies have moved to Virginia, further increasing the population. For our project, we will be using two datasets. The first is the Opioid Addiction Dataset from the Virginia Department of Health (VDH). The second dataset is the Forensic Epidemiology Dataset for Opioids produced by the Office of the Medical Examiner for Virginia. We will use these datasets to evaluate and find out the relationship between

unnatural fatalities due to opioids and the health preparedness and emergency response by counties.

II. Literature Review:

There is very little literature on our subject specifically. The NIH [2] has produced opioid death data and summaries by state, but this data doesn't delve deeper by state as it does not differentiate by county. However, the literature tells us that the rate of fatalities due to opioids in Virginia is higher than the national average, 13.5 per 100,000 versus 13.3 per 100,000. While it is a small difference, for a population the size of Virginia, simply reducing the rate to the national average would save 16 lives each year. In addition to the death rate, the NIH found that the number of heroin-related fatalities in Virginia has had a 1000% increase since 2010. Despite the insight provided, the NIH research highlights the differences in deaths for only three categories, heroin, prescription opioids, and synthetic opioids [1]. We propose to look at the differences in fatalities within five groups: prescription opioids, fentanyl, heroin, benzodiazepine, and cocaine. This could show trends for other opioid drugs as well to determine if this trend is purely towards heroin or for non-prescription opioids in general.

Also, Pennsylvania State University published a paper titled 'Crime Rate Inference from Big Data' [3]. In it, they use a large amount of urban data to inference areas of crime based on demographics, city planning, and micro-events. The paper includes statistical inference and how geographical inference can be used to show the spread or linkage of events. This method could be useful for looking at the range of opioid fatalities in general, or individual drugs, by county. Tracking this is important due to emergency service and hospital preparedness. If a county is aware of connections that suggest a future rise or fall in the use of a particular drug, that information can be used to make their services more efficient and potentially save lives. Also, if police divisions - which cover multiple counties -

find clusters of drugs use that crossdivision lines, they will be more prepared to handle such more significant case.

For past research into state fatalities, the research has been done using information on particular patients, their opioid prescription history, medical record, and hospital admittance records. One example, Allegheny County, PA has tracked fatal opioid overdoes by victim demographic information, residential zip code, and zip code where the body was recovered [9]. This provides information within the county similar to the research we will do within the state. However, since not all counties in PA have provided such information, they do not have a state-wide tracking system based on county. Also, this information is merely about the fatal overdose and does not involve the police division, hospital response, or other information that is covered in our data sets and project.

Another difficulty found in the literature is that tracking opioid use and overdoses, fatal or otherwise, is done using patient information. Due to privacy issues and national versus state laws involving drug tracking, states are not uniform in their tracking requirements. While 49 states in addition to D.C. have a Prescription Monitoring Program, the laws and regulations regarding the usage of that data are not uniform by state. For instance, many states do not require real-time updates despite the benefit this would have. When Oklahoma began requiring real-time updates on prescription opioids, the fatalities dropped by approximately 20%, and they went from 10th to 20th on the ranking of fatalities per 100,000 by state [8]. Virginia on the other hand only requires reporting within 7 days. Since there is a lack of real-time data, tracking country trends may provide better insight into where issues may occur by locating hot spots.

KPMG published a report in 2017 [10] summarizing the data-driven case studies focusing on opioid fatalities In the United States, following a presidential mandate for research into the subject. The report looks at the general challenges of the crisis, including how decreasing prescription opioid fatalities by limiting access increases fatalities from other sources such as heroin, as well as trends. It further discusses the five major approaches used as of November of 2017. These approaches include getting more consistent data, unifying and improving reporting for PMP information nationally, using predictive data about individuals with prescriptions to detect possible overuse and addiction, and tracking location data by neighborhood in conjunction with an individual's private medical information. In case studies published since the research into these areas has improved, but we have not seen any research by this point that suggests tracking by county, especially in conjunction with hospital response or police department information. This makes out proposal unique at this time.

III. Data Set:

Data Set 1: Opioid Addiction Dataset from the Virginia Department of Health (VDH)

Year	FIPS Cod	Locality	Source	Type	Case Count Display	Rate	VDH Health District	VDH Health District Case Count Display	VDH Health District Case Rat	VDH Health Region
2011	51001	Accomack	ED	ED Heroin (	0	0	Eastern Sho	0	0	Eastern
2011	51003	Albemarle	ED	ED Heroin (	0	0	Thomas Jeff	0	0	Northwest
2011	51005	Alleghany	ED	ED Heroin (	0	0	Alleghany	0	0	Southwest
2011	51007	Amelia	ED	ED Heroin (	0	0	Piedmont	0	0	Central
2011	51009	Amherst	ED	ED Heroin (	0	0	Central Virg	0	0	Southwest
2011	51011	Appomatto	ED	ED Heroin (	0	0	Central Virg	0	0	Southwest

VDH Health Region	VDH Health Region Case Count Display	VDH Health Region Case Rat	Virginia Hospital & Healthcare Preparedn ess Regic	Virginia Hospital & Healthcare Preparedn ess Region Case Count Display	Virginia Hospital & Healthcare Preparedn ess Region Case Rat	Virginia Departme nt of Emergency Manageme nt Regio	Virginia Departme nt of Emergency Manageme nt Region Case Count Display	Virginia Departme nt of Emergency Manageme nt Region Case Rat
Eastern	0	0	Eastern	0	0	Tidewater	0	0
Northwest	0	0	Northwest	0	0	Central Virg	0	0

Communit y Service Board Case Count Display	Communit y Service Board Case Rate	Virginia State Police Division	Virginia State Police Division Case Count Display	Virginia State Police Division Case Rat	Virginia State	Virginia State Case Count Display
0	0	VSP Divisior	0	0	Virginia Stat	0
0	0	VSP Divisior	0	0	Virginia Stat	0
0	0	VSP Divisior	0	0	Virginia Stat	0

Figure (a) Data Set 1

Data Set 2: Forensic Epidemiology Dataset for Opioids produced by the Office of the Medical Examiner for Virginia

	2007		2008		2009		2010	
Locality of Injury	n	rate	n	rate	n	rate	n	rate
Accomack County	2	5.2	0	0.0	2	5.2	1	3.0
Albemarle County	2	2.1	3	3.2	5	5.3	5	5.1
Alexandria City	5	3.6	11	7.6	12	8.0	2	1.4
Alleghany County	1	6.1	1	6.2	1	6.2	2	12.3
Amelia County	0	0.0	0	0.0	0	0.0	0	0.0
Amherst County	3	9.3	2	6.1	1	3.1	2	6.2
Appomattox County	0	0.0	0	0.0	0	0.0	0	0.0

2015		2016		2017		2018* (preliminary)	TOTAL (excludes 2018)	
n	rate	n	rate	n	rate	n	n	rate
1	3.0	5	15.2	1	3.1	3	27	7.1
3	2.9	3	2.8	6	5.6	4	39	3.5
7	4.4	8	5.1	10	6.2	8	92	5.6
2	12.9	2	12.8	1	6.6	0	15	8.5
0	0.0	1	7.7	2	15.4	0	5	3.5
0	0.0	3	9.5	2	6.3	0	17	4.8
1	6.5	3	19.4	0	0.0	0	6	3.6

Figure (b) Data Set 2

IV. Types of Data Measurement scale:

DATA SET 1:

ATTRIBUTE	MEASURE
YEAR	Nominal
FIPS CODE	Nominal
LOCALITY	Nominal
SOURCE	Nominal
TYPE	Nominal
CASE COUNT DISPLAY	Ratio
RATE	Ratio
VDH HEALTH DISTRICT	Nominal
VDH HEALTH DISTRICT CASE COUNT DISPLAY	Ratio
VDH HEALTH DISTRICT CASE RATE	Ratio
VDH HEALTH REGION	Nominal
VDH HEALTH REGION CASE COUNT DISPLAY	Ratio
VDH HEALTH REGION CASE RATE	Ratio
VIRGINIA HOSPITAL & HEALTHCARE PREPAREDNESS REGION	Nominal
VIRGINIA HOSPITAL & HEALTHCARE PREPAREDNESS REGION CASE COUNT DISPLAY	Ratio
VIRGINIA HOSPITAL & HEALTHCARE PREPAREDNESS REGION CASE RATE	Ratio
VIRGINIA DEPARTMENT OF EMERGENCY MANAGEMENT REGION	Nominal
VIRGINIA DEPARTMENT OF EMERGENCY MANAGEMENT REGION CASE COUNT DISPLAY	Ratio
VIRGINIA DEPARTMENT OF EMERGENCY MANAGEMENT REGION CASE RATE	Ratio
COMMUNITY SERVICE BOARD	Nominal
COMMUNITY SERVICE BOARD CASE COUNT DISPLAY	Ratio
COMMUNITY SERVICE BOARD CASE RATE	Ratio
VIRGINIA STATE POLICE DIVISION	Nominal
VIRGINIA STATE POLICE DIVISION CASE COUNT DISPLAY	Ratio
VIRGINIA STATE POLICE DIVISION CASE RATE	Ratio
VIRGINIA STATE	Nominal
VIRGINIA STATE CASE COUNT DISPLAY	Ratio
VIRGINIA STATE CASE RATE	Ratio

DATA SET 2:

ATTRIBUTE	MEASURE
LOCALITY OF INJURY	Nominal
2007	Ratio
2008	Ratio
2009	Ratio
2010	Ratio
2011	Ratio
2012	Ratio
2013	Ratio
2014	Ratio
2015	Ratio
2016	Ratio
2017	Ratio
2018* (PRELIMINARY)	Ratio
TOTAL (EXCLUDES 2018)	Ratio

V. Data Description:

DATA SET 1:

Attributes: 28 attributes
Dataset size: 7448 column and 28 rows
File Size: 995.12 KB

DATA SET 2:

Attributes: 14 attributes
Dataset size: 141 column and 14 rows
File Size: 43.49 KB

VARIABLES

We use four separate measures that serve as proxies for different aspects of the opioid crisis, including:

- Death Due to Opioid type
- Data on VDH Health Region
- Data substance fatality Rate
- Data by State Police Division

These indicators do not directly measure opioid misuse or opioid use disorder; however currently no local measures exist that are nationally representative.
Data on Opioid Fatality comes from the Virginia Department of Health(VDH); the data contain fatality due to any substances, Death Due to Opioid type, Data on VDH Health Region, Data on substance fatality rate, Data by State Police Division produced.

Opioid-Related Hospitalizations

Data on hospital stays and emergency department visits related to opioids were drawn from the Virginia State Inpatient Databases and collected as part of the Healthcare Cost and Utilization Project from the Agency for Healthcare Quality and Research.

Hospital inpatient stays and emergency department visits are non-duplicative: patients admitted to the hospital after visiting the ER are considered a hospital stay and removed from the ED visit. Data were available for Virginia , for the years 2011 through 2017. Patient records were aggregated to the county of patient residence and calculated as rate per year. Separate data are reported for several categories of substances.

VI. Software Required:

- ❖ SQL*Plus
- ❖ Python
- ❖ R Studio
- ❖ Tableau

SQL*PLUS - SQL*Plus is used to perform different tasks like retrieve, update or delete the data from the database. In SQL we are going to join our datasets and explore the data using simple standard commands such as Insert, Drop, Select, Update, and Delete.

Python - Python is a general-purpose programming language, and high-level language. It provides a clear program for both large- and small-scale companies. Python is used in processing the data such as cleaning, manipulating, and visualization.

R Studio - It is a free and open source with an integrated environment. R Studio is used for graphics and statistical computing. Here we are using R Studio for graph, correlation and to summarize the data.

Tableau - Tableau is the most secure, flexible and powerful end-to-end analytic platform. Tableau is used to analyze and visualize the data.

Power BI – It provide business intelligence and interactive visualization with an end user interface where they can create their own reports.

VII. Potential Questions:

The questions that we are trying to answer are as follows:

- ➢ How do the opioid-based fatalities vary by health region (county) in Virginia?
- ➢ Is there a relationship between health preparedness region case rates and community service board cases related to opioids over time?
- ➢ How does the change in opioid fatalities vary by police division over time?
- ➢ How does the rate of fatal overdoses vary by police division and health region in regard to opioid fatalities?
- ➢ What percentage of opioid fatalities are caused by prescription opioids and has this changed over time?
- ➢ What trends exist in non-prescription opioid fatalities versus prescription opioid fatalities over time?
- ➢ What trends exist for mortality rates by health region and event type?

The expected outcome of the project would be to answer the questions above to gain a better understanding of how opioid fatalities have changed in Virginia in the last decade, by county. The answer will be supported by the data alongside visualization and can be used by police departments, hospitals, and policymakers in Virginia at the state or county levels to prevent further unnatural fatalities due to opioid use.

VIII. Data Processing:

The first step when cleaning our data was done by removing the data where the 'Type' value, denoting cause of death, was not directly linked to an opioid. These removed values include being HIV positive reports of Hepatitis B and Hepatitis C, Neonatal Abstinence Syndrome, and being treated with Narcan in the ambulance. This was done in R studio by producing a subset of the original data set without these specific values using the subset() function.

```
Step1 <- subset(Data, Data$Type != "EMS Narcan" & Data$Type != "Diagnosed HIV" & Data$Type != "Reported Hepatitis C (18-30 year olds)" & Data$Type != "Neonatal Abstinence Syndrome")
```

Cleaned dataset:

	Locality	Year	FIPS Code	Source	Type	Case Cour	Rate	VDH Healt	VDH Healt	VDH Healt	VDH Healt	VDH Healt	VDH Healt	Virginia H	Virginia H	Virginia H	Virginia D	Virginia D	V
8	Accomack	2011	51001	ED	ED Heroin	0	0	Eastern Sh	0	0	Eastern	0	0	Eastern	0	0	Tidewater	0	
12	Accomack	2011	51001	ED	ED Opioid	0	0	Eastern Sh	0	0	Eastern	0	0	Eastern	0	0	Tidewater	0	
17	Accomack	2011	51001	OD Death	Fatal Fent	NA	3	Eastern Sh	NA	2.2	Eastern	46	2.5	Eastern	46	2.5	Tidewater	46	
26	Accomack	2011	51001	OD Death	Fatal Presc	NA	3	Eastern Sh	NA	2.2	Eastern	89	4.9	Eastern	89	4.9	Tidewater	88	
39	Albemarle	2011	51003	OD Death	Fatal Fent	0	0	Thomas Je	0	0	Northwest	23	1.8	Northwest	21	2.5	Central Vi	5	
48	Albemarle	2011	51003	ED	ED Heroin	0	0	Thomas Je	0	0	Northwest	0	0	Northwest	0	0	Central Vi	0	
50	Albemarle	2011	51003	ED	ED Opioid	0	0	Thomas Je	0	0	Northwest	0	0	Northwest	0	0	Central Vi	0	
53	Albemarle	2011	51003	OD Death	Fatal Presc	NA	2	Thomas Je	NA	1.7	Northwest	85	6.8	Northwest	63	7.4	Central Vi	27	
70	Alleghany	2011	51005	OD Death	Fatal Presc	0	0	Alleghany	8	4.5	Southwest	163	12	Near Sout	71	7.2	Roanoke /	56	
73	Alleghany	2011	51005	ED	ED Heroin	0	0	Alleghany	0	0	Southwest	0	0	Near Sout	0	0	Roanoke /	0	
74	Alleghany	2011	51005	ED	ED Opioid	0	0	Alleghany	0	0	Southwest	0	0	Near Sout	0	0	Roanoke /	0	
75	Alleghany	2011	51005	OD Death	Fatal Fent	0	0	Alleghany	NA	1.1	Southwest	17	1.3	Near Sout	13	1.3	Roanoke /	12	
91	Amelia	2011	51007	ED	ED Opioid	0	0	Piedmont	0	0	Central	0	0	Central	0	0	Richmond	0	
93	Amelia	2011	51007	ED	ED Heroin	0	0	Piedmont	0	0	Central	0	0	Central	0	0	Richmond	0	
106	Amelia	2011	51007	OD Death	Fatal Fent	0	0	Piedmont	0	0	Central	44	3.2	Central	44	3.2	Richmond	44	
109	Amelia	2011	51007	OD Death	Fatal Presc	0	0	Piedmont	NA	1.9	Central	66	4.8	Central	66	4.8	Richmond	63	
125	Amherst	2011	51009	ED	ED Heroin	0	0	Central Vi	0	0	Southwest	0	0	Near Sout	0	0	Central Vi	0	
128	Amherst	2011	51009	OD Death	Fatal Fent	0	0	Central Vi	NA	0.8	Southwest	17	1.3	Near Sout	13	1.3	Central Vi	5	
130	Amherst	2011	51009	ED	ED Opioid	0	0	Central Vi	0	0	Southwest	0	0	Near Sout	0	0	Central Vi	0	
131	Amherst	2011	51009	OD Death	Fatal Presc	NA	3.1	Central Vi	8	3.1	Southwest	163	12	Near Sout	71	7.2	Central Vi	27	
154	Appomatt	2011	51011	OD Death	Fatal Presc	0	0	Central Vi	8	3.1	Southwest	163	12	Near Sout	71	7.2	Central Vi	27	
155	Appomatt	2011	51011	ED	ED Heroin	0	0	Central Vi	0	0	Southwest	0	0	Near Sout	0	0	Central Vi	0	
158	Appomatt	2011	51011	ED	ED Opioid	0	0	Central Vi	0	0	Southwest	0	0	Near Sout	0	0	Central Vi	0	

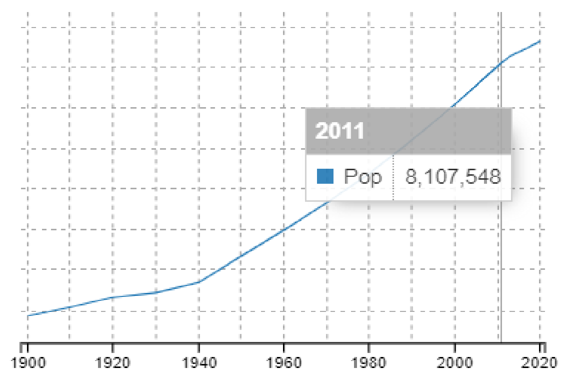
Figure(c) Cleaned Data Set 1

The second step was in locating missing values. Still in R studio Using is.null and the which() function, 38 NA values were found. There were 2257 other missing values denoted by an asterisk (*), all in the case count display columns. The variables and number of missing values are shown in the table below. There are no missing values in the corresponding rate columns for these variables. The counts represent deaths due to overdose on a specified opioid and the rate is the mortality rate per 100,000. To correct for these missing values, the pared down dataset was loaded into SQL*Plus and joined with Data Set using the Locality/County columns. In addition, population values from the last census were included as a new column. The missing counts were calculated using known rates for each drug type, the general count for all drug types, and the population for each county. Due to the rate being rounded to one significant figure, the error when using known counts and rates to determine missing values is approx. 28%. This error is consistent across all variables and counties so will affect all groups in a consistent manner. Considering the above, this method is what is used to replace the na values in our data set.

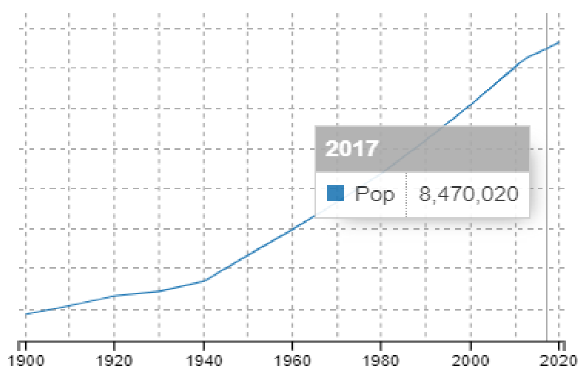
Variable Name	Number of Unknown Values	Original Filler for NA/Missing values
Case Count Display	910	*
VDH Case District Health Count	553	*
Virginia Hospital & Healthcare Preparedness Region Case Count Display	60	blank
Virginia Department of Emergency Management Region Case Count Display	38	NA
Community Service Board Case Count Display	671	*
Virginia State Police Division Case Count Display	73	*

IX. Data Exploration:

To explore how a counties' conditions, relate to the opioid crisis in Virginia, we examine geographic and statistical relationships between indicators of VDH Health Region, substance fatality rate, State Police Division, and prevalence of the following opioids: Heroin, Fentanyl, and Prescription Opioids and other non-prescription opioids. For each region or grouping which provided by VDH, such as Health district or police divisions, we are giving both counts and rates. As mentioned in the introduction and shown in the graph below, the population in Virginia has been increasing dramatically.



Figure(d) Population in Virginia State in 2011

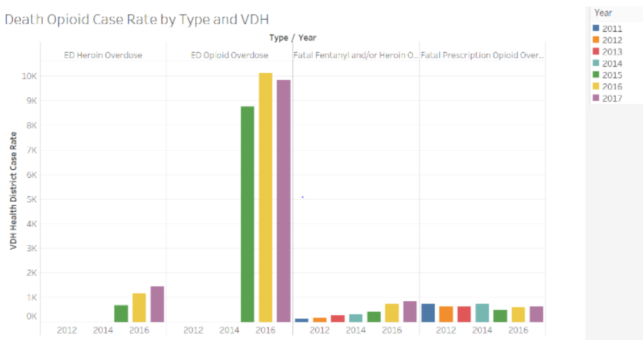


Figure(e) Population in Virginia State in 2017

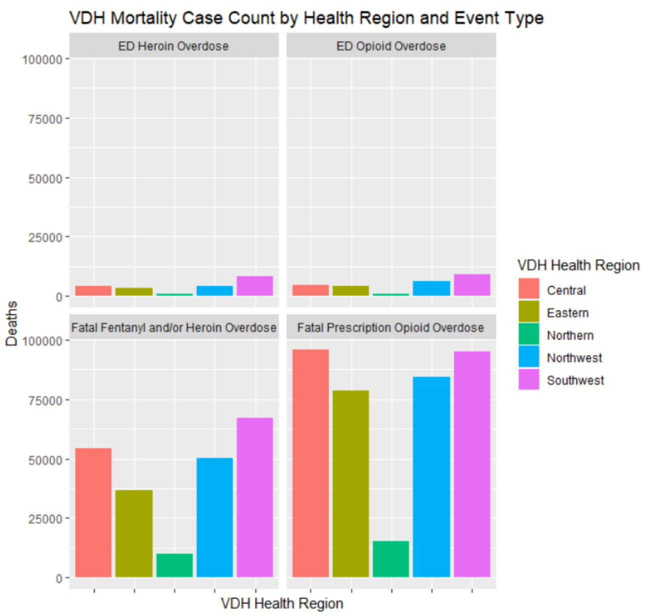
We also analyzed data from 2011 through 2017 for all counties in Virginia in the U.S.

The first stage when exploring the data was to look for trends by health region and type of opioid. The graph below shows the mortality case count, also known as number of deaths, for each region by opioid type. These values present the total of deaths by opioid type and region between for 2011 and 2017**.**

As seen in Figure(f), Overall, the last several years, the number of deaths due to ED opioid overdose is significantly much higher than the other type of opioids. Also, the count of death due to fatal fentanyl or Heroin overdose has constantly increased.

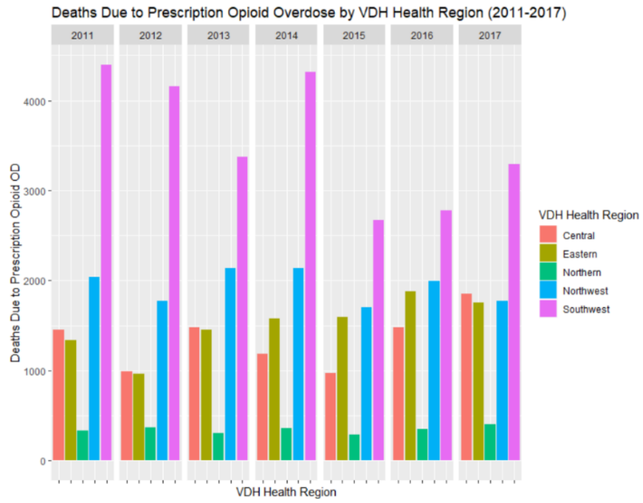


Figure(f) Death Opioids by Type and Date in VA State



Figure(g): VDH Mortality Case Count by Health Region and Event Type

As seen above, the number of deaths due to Heroin and other opioids are significantly lower than for Fentanyl and/or Heroin and Prescription Opioids. Further exploration shows that the first two categories were not recorded before 2015, which is when more priority was made for tracking opioids. A review of the literature shows that there is a trend nation-wide between prescription opioid and fentanyl and/or heroin use. To test if this trend appears for their related fatalities is Virginia, graphs of deaths by region from 2011-2017 were created.



Figure(h): Deaths Due to Prescription Opioid Overdose by VDH Health Region (2011-2017)

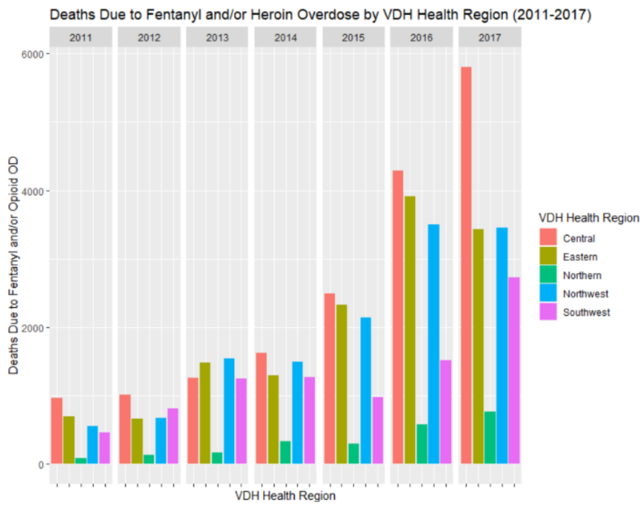
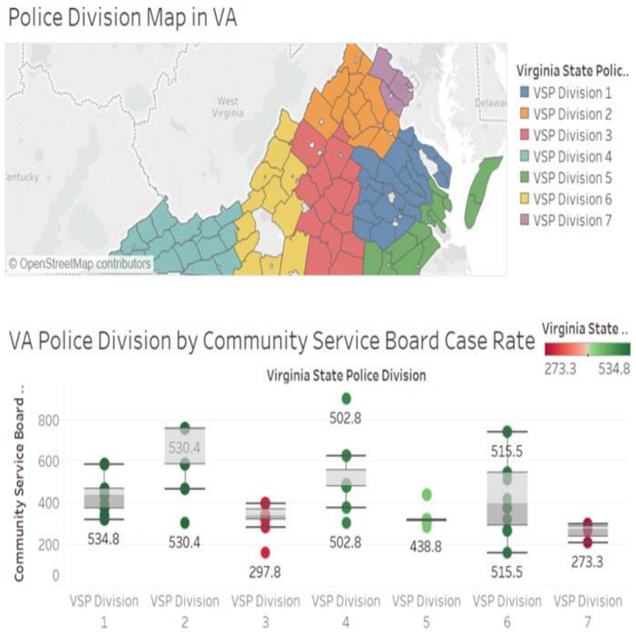


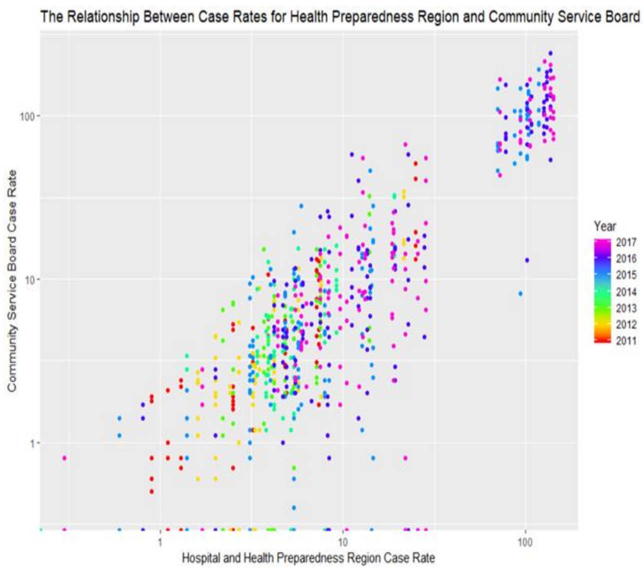
Figure (i): Deaths Due to Fentanyl and Heroin Overdose by VDH Health Region (2011-2017)

Our data supports this trend, though deaths due to prescription opioids had a decrease from 2014 to 2015 and then has remained fairly steady aside from the Southwest region, which decreased significantly but then increased again. This increase in count is likely due in part to a population increase, but it is not clear from our data. The deaths due to fentanyl/heroin overdoses in turn have seen a sharp increase over time, corresponding to the decrease in overdoses due to prescription opioids. The death rates are a good indicator of overall use as well since higher usage leads to a greater number of deaths. As a caveat, fentanyl is the most deadly opioid thus we are looking at counts and rates alone and not as an indicator of usage. No known relationship between fentanyl overdose rates and usage is available in the literature at this time. The timing of the change in death counts align with the crack-down on prescription opioid use and the full scale use of the Prescription Opioid Tracking System initiated by the US government as a state requirement in 2015. This inverse relationship between prescription opioid and fentanyl/heroin deaths variation will be further explored when comparing the community service board case rate change by county and state police divisions to determine if those grouping provide further insight into this variation. Community service boards are an important indicator of community response to the crisis since community service boards only started tracking opioid fatalities in their borders when fatalities started to increase in the 2000's. Some boards still do not track fatalities if the counts are low in their district. This is because they have not been asked to provide funding or public education by the local health districts.



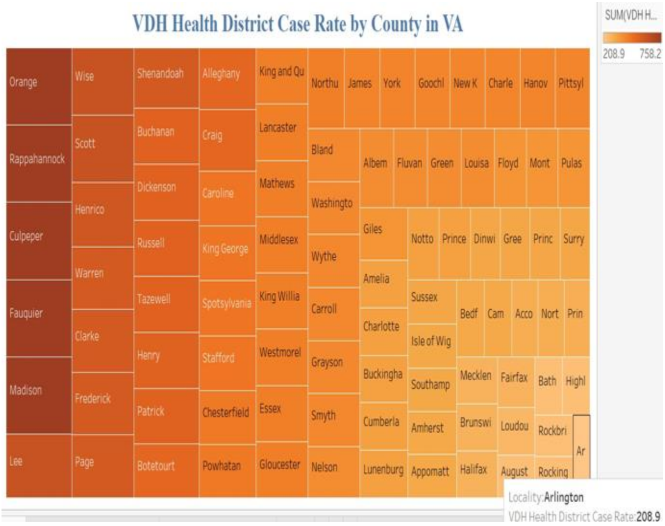
Figure(j): Deaths Due to Community Service Board Case Rate by Police Division

The graphs above were provided using Tableau. The boxplots indicate the spread in community service board counts by state police division. Zero values have been removed when making this blot to avoid outliers. The first notable feature is Division 5, which has a very small IQR and thus has one outlier. This means that, aside from one year, their rates were very consistent. The 3rd and 7th Police Divisions also have lower rates compared to the rest of the state and are fairly consistent. The most densely populated region is Division 7 and it is a largely metropolitan area, so it is interesting that its community service rates are so low and it is something to look into given the last graph in Figure(j) also showed low fatality counts for the region. To further explore the relationship between community service boards and other indicators, a scatterplot matrix was created. From it, the most significant and highly correlated graph was selected for further exploration, shown below.



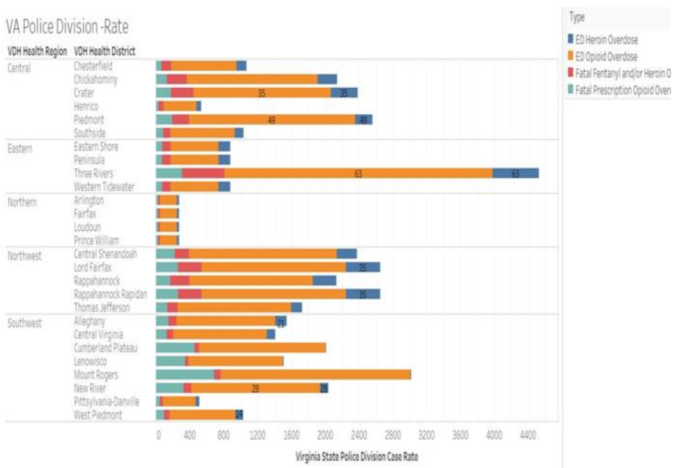
Figure(k): Relationship between Case Rate for Health Preparedness Region and Community Service Board

The relationship between case rates for health preparedness region and community service board was the most significant, though the rates were highly clustered around lower values. A log transformation was used on both axis to enhance clarity and highlight the relationship. The transformed model has an R^2 of 0.87 and is statistically significant. The zero values in the graph mean that the community service board was not tracking the rates, not that the rates were zero. These values were included still to show that community service boards which were not measuring the fatalities in their area were not isolated to only low case rates for the hospital and health preparedness region and that even in 2017 some boards were not counting fatalities. As mentioned above, this means that in some counties, community service boards are not involved in funding nor in public education. These counties could be of interest to the VDH when trying to encourage participation in public health programs across the state.



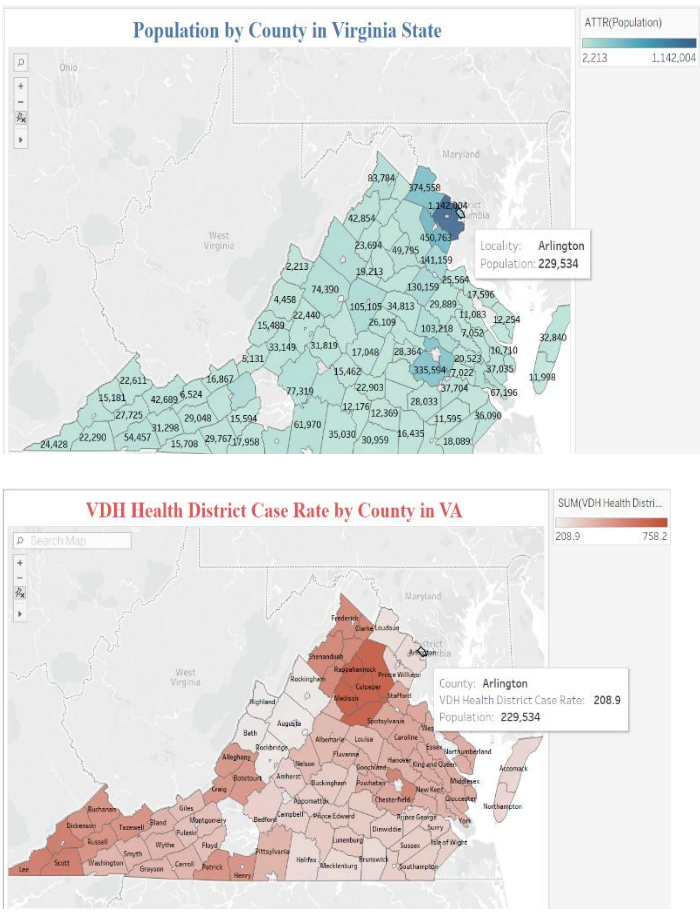
Figure(l): VDH Health District Case Rate by County in VA

The health district case rates are shown here by county as a sum total of rates from 2011 to 2017. The district with the highest cumulative case rate has a rate 364% higher than the lowest highest, which is a significant spread. The districts with the highest case rates are clustered mainly in the Northwestern part of the state and the regions with the lowest rates are in the Northern and Central parts of the state. This supports the conclusions above about which regions have the highest counts, since health districts have different dividing lines and still highlight the same regions has having significant rates, either extremely high or very low. To further highlight the variation by health region as well as to further explore the differences by police division shown in [figure(j)] a stacked bar plot of police division case rates by opioid, displayed with the corresponding health region and district is provided.



Figure(m): VA Police Division-Rate

In figure(m), The plot shows that each region has variety amongst its districts and thus district rates can provide more insight than region aggregates. For instance, Three Rivers in the Eastern Health Region is an outlier for the region and an aggregate would should much higher values because of it. In counterpoint, the Northern region is extremely consistent between districts and an aggregate would be very accurate. Still, a view by district is more clear. Between all regions, the opioid type causing the most fatal overdoses is non-prescription opioids. This aligns with the literature review for trends in opioid use in the state since non-prescription opioid use as increased due to increased controls on prescription opioids. One last interesting point in the graph is that the heroin fatality rates are extremely low in many counties in the Southwest region. This may be due to having fewer metropolitan areas, lower average income, or other factors not explored in our study.



Figure(n): Population and VDH Health District Case Rate by each county in VA

In figure(n), the final pair of graphs were provided in Tableau and show the health district case rate and population by county. This pair highlights the importance of looking at both case rates and population to get a more full understanding of what is happening in a particular area. For instance a region of the state that includes Bath and Rockingham has very low case rates. Given that they have similar populations compared to surrounding count, the counts in these districts are rather low. This region is one that police and health departments might want to explore to see why the rates are so low. If they have certain policies or other differences it can be used to help other counties in the region that are similar. Also, the Southwest region has rates that are as high as rates for regions with much higher populations and denser populations. Finally, Northern Virginia has fairly low rates. In figure(n) the case counts for Northern Virginia were shown, so this further highlights how this part of the state has fewer fatalities.

Conclusion

The data exploration and analysis has showed statewide and local trends on opioid fatalities in Virginia. These trends can be used to predict further increases or decreases in opioid fatalities. These predictions in turn can be used to inform policy when confronting the opioid crisis at a state level, as well as to better support hospitals at the district and local levels when allocating funding and resources.

The following are some of the general conclusions about opioid fatalities in Virginia. Fentanyl, Heroin, and Prescription Opioids have caused the most deaths throughout the state, and while Heroin is less common in a few counties this is fairly consistent. The data shows a trend in the decrease of fatalities due to prescription opioids, and thus its use, in favor of usage of, and subsequent fatalities due to, heroin and fentanyl. Given that fentanyl is 10-100% more fatal than heroin and the number of fatalities is increasing, it is important that both police divisions and health departments are able to make informed decisions to prevent more opioid related fatalities. Another point is that despite the high population, the Northern region of Virginia has low fatality rates for all opioids when compared to other regions. This is also true at the county level. Given that Arlington has the highest population by county in the state and yet still a lower rate and count, exploration should be done to determine what is being done well, or is part of the demographics and culture of the area, to lead to these rates. The last point is that there are still outliers in every trend, as shown in each graph and step in our data exploration. These outliers can be further explored to determine why that area in particular has such different rates when compared to surrounding areas.

Further Research

The dataset for this project used aggregates by count for various regions and districts as provided by VDH. If data was gather with more specific location information at a county level clustering analysis could be done to discover trends and where opioid usage may cross county and police division lines. In addition, there were many outliers in the data and differences between regions. Our exploration of the data explains what the differences are but does little to explain why it is the case. Additional data on demographics such as income, education, and other census data could be used to further determine the relationship between certain indicators and opioid fatalities. Finally correlation analysis could be done with this enhanced data set between drug usage in an area. By this, I mean the inverse relationship between fentanyl/heroin and prescription opioid could be further explored and quantified. All research can also be more accurate as the amount of data increases. However, given that this crisis is relatively new and most sources do not track it beyond 2010 or 2011 as the VDH does, this merely means that models and analysis will grow stronger with time as the dataset grows.

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