Juan J. Nunez
DATA 205 – Final Report
May 2019

Data Stories:

The following data stories are synthesized from the three main datasets from the final report analysis. Each dataset (i.e., traffic violations, crime, and bias incidents) will have its own story. The overarching theme of the stories is *Understanding Different Types of Incidents in Montgomery County*.

1. Traffic Violations:

The descriptive statistics for the variables used in the analysis are below.

Most individuals involved in traffic stops were white (35.5%) as opposed to other races/ethnicities. Men were more often involved in traffic stops than women (67.08%). Surprisingly, alcohol was seldomly involved in traffic incidents (0.15%). The district with the highest number of traffic stops was 4D Wheaton (25.65%).

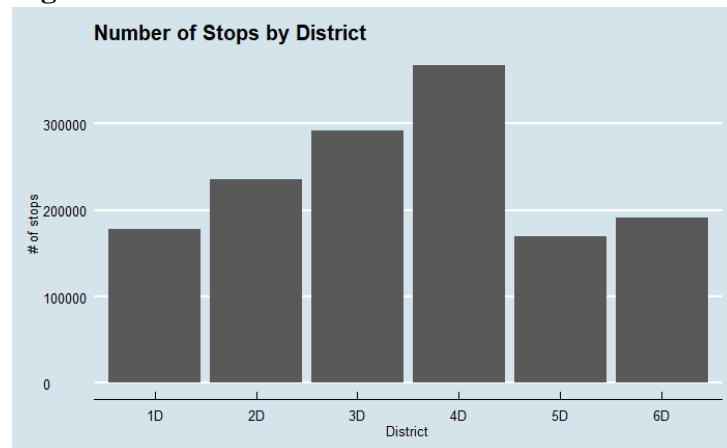| Traffic:	N	%
1. Race:		
Asian	86,804	5.86%
Black	469,316	31.68%
Hispanic	315,896	21.32%
White	525,855	35.5%
Other	83,570	5.64%
2. Gender:		
Female	487,115	32.92%
3. Alcohol (Yes)	2,292	0.15%
4. District:		
1D Rockville	177,628	12.4%
2D Bethesda	235,207	16.42%
3D Silver Spring	291,705	20.37%
4D Wheaton	367,336	25.65%
5D Germantown	169,374	11.82%
6D Gaithersburg	191,104	13.34%

Figure 1.

Figure 1 above is a basic bar graph with the number of traffic stops for each district. As the descriptive statistics for police district show, 4D Wheaton has more stops than any other district. At first glance, we would expect 4D Wheaton to also contain a relatively high number of alcohol-related traffic stops. This expectation is the source inspiration for Figure 2 below. As can be seen in Figure 2, not only is 4D Wheaton not the district with the highest number of alcohol-related traffic stops, it is not even close to the district with the highest number of alcohol-related traffic stops. The district with the highest number of alcohol-related traffic stops is 5D Germantown, the district with the least amount of overall traffic stops. The latter finding is

very interesting. It is strange that when a filter (i.e., alcohol-related stop) is applied to this data, we see a completely different association between number of stops and district.

Figure 2.
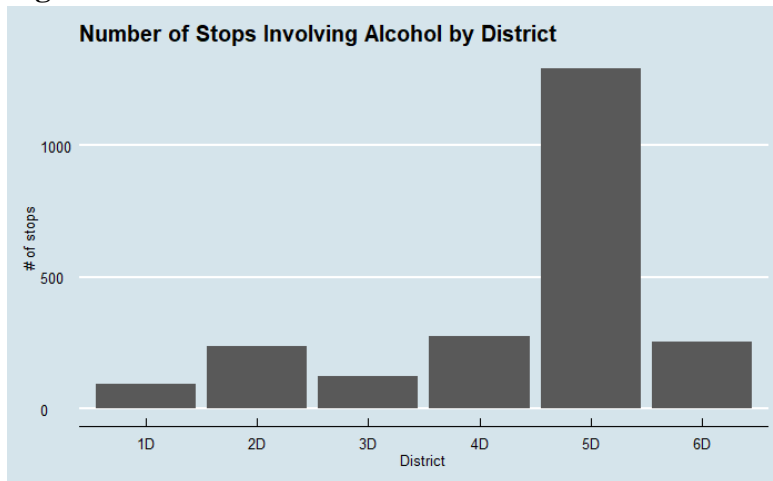
It is outside of the scope of this analysis to test why there are so many alcohol-related stops associated with 5D Germantown but it is a great starting point for any type of research focused on transportation in Montgomery County. A possible reason could be that public transportation in Germantown reaches less people. Another reason could be culture. With a proper survey analysis, these hypotheses could be tested. Figuring out why the distribution of traffic stops vary according to different types of stops could potentially save a lot of lives and insurance dollars so it should be explored in the future.

Figure 3.
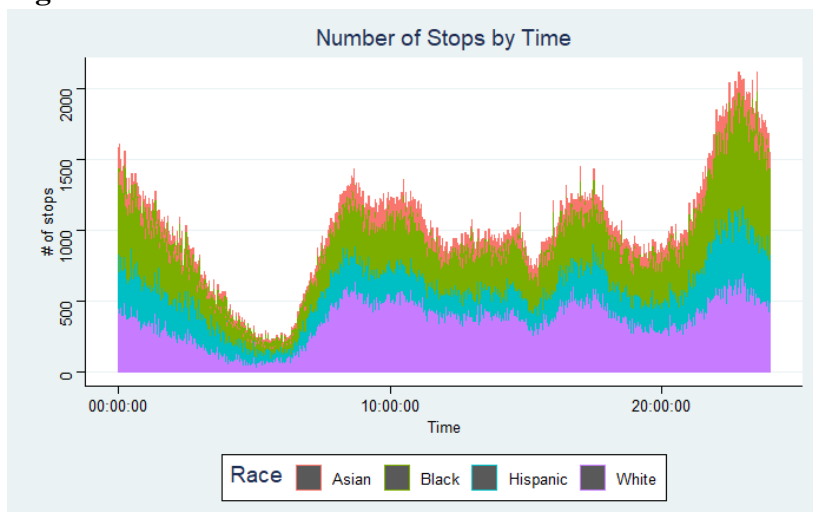
In a similar way, the distribution of traffic stops according to race/ethnicity can also be deceiving. While whites had the highest number of traffic stops, the story changes completely once we take into consideration time of stop. As can be seen in Figure 3, there is an increase in number of stops after 20:00:00 but this increase is much more pronounced for blacks and Hispanics in that order. This is evidence that blacks and Hispanics tend to be involved in traffic stops more often between 20:00:00 and 02:00:00 than during other times of the day. Unfortunately, it is not possible to know why this within group difference according to time exist with the current available data. Perhaps this is something advocacy groups and those responsible for the traffic stops themselves should investigate further.
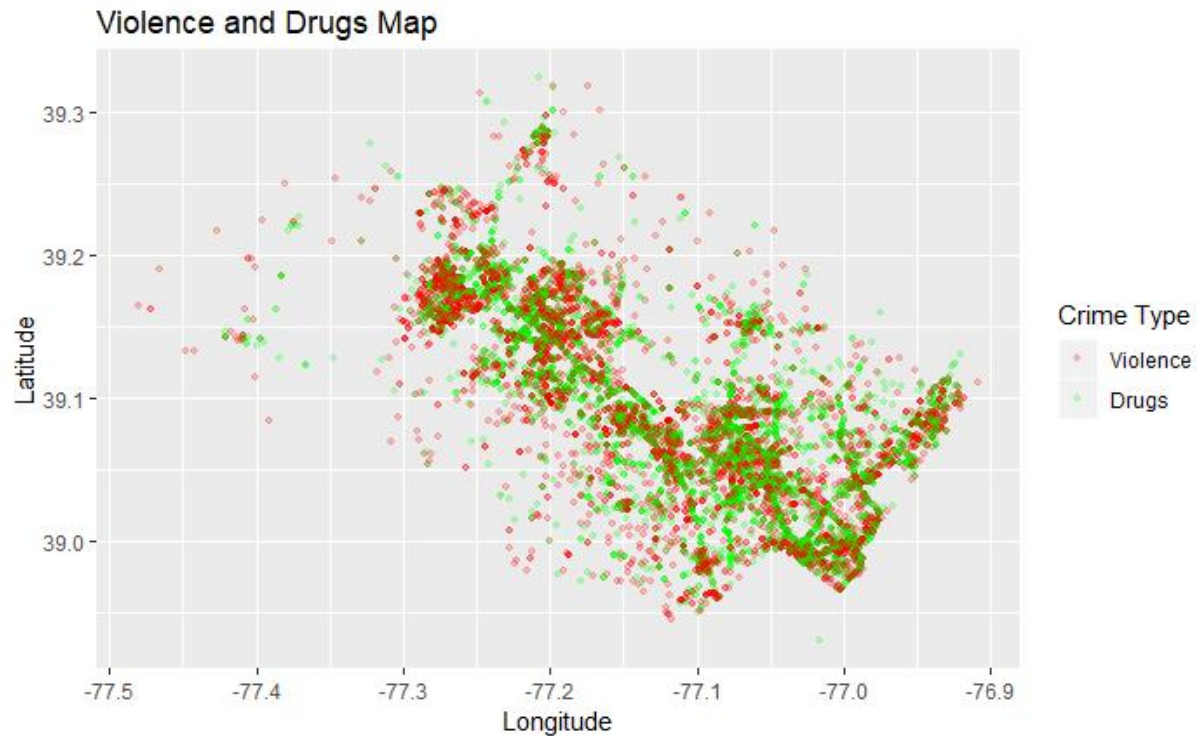
2. Crime:

The descriptive statistics for the variables used in the analysis are below.

Crime:	N	%
1. Crime against:		
Person	7,335	9.75%
Property	30,312	40.30%
Society	21,535	28.63%
Other	16,026	21.31%
2. Crime Type		
Drugs	8,858	11.77%
Violent	8,722	11.59%
Other	57,652	76.63%
3. District		
1D Rockville	10,448	14.23%
2D Bethesda	9,974	13.58%
3D Silver Spring	15,915	21.67%
4D Wheaton	14,788	20.14%
5D Germantown	9,905	13.49%
6D Gaithersburg	12,413	16.90%

The majority of crimes reported were property crimes (40.30%). A little over 23% of the crimes were drug and violence related. The district with the most crimes was 3D Silver Spring (21.67%) with 4D Wheaton coming at a close second (20.14%). The districts 1D Rockville, 2D Bethesda, and 5D Germantown had similar crime levels at around 14%. The district 6D Gaithersburg accounted for approximately 17% of the crime in Montgomery County.

As can be seen in Figure 4 below, we clearly see how drug and violent crimes differ in location. It is evident that drug crimes tend to follow along major roads (i.e., 270 N, Georgia avenue, etc.) while violent crimes tend to be concentrated in pockets with many occurrences also being more spread out throughout the county. We can see that Germantown has many violent

Figure 4.

Violence and Drugs Map

crimes because we see a large concentration of red dots in that area. Using Figure 4, we find evidence that even though drug and violent tend to be compromised of similar percentages of the total crime in the area, their distribution is completely different.

Part of doing research involves using multiple tools and seeing which one works better. It is for that reason that I created a map in Tableau Public using the same information as Figure 4. As can be seen below, Figure 5 is a static version of the Tableau Public version of Figure 4.

We can see that it appears to be a bit slicker than the R rendering (i.e., Figure 4). But this does not come without a price. While the roads we observed in Figure 4 are still visible in Figure 5, they are much less pronounced. Moreover, R automatically adds the latitude and longitude on the x and y axes, so it is easier to analyze quadrants. What Figure 5 on Tableau Public has going for it is that a) it is interactive and b) the red pockets are more identifiable.

Figure 5.
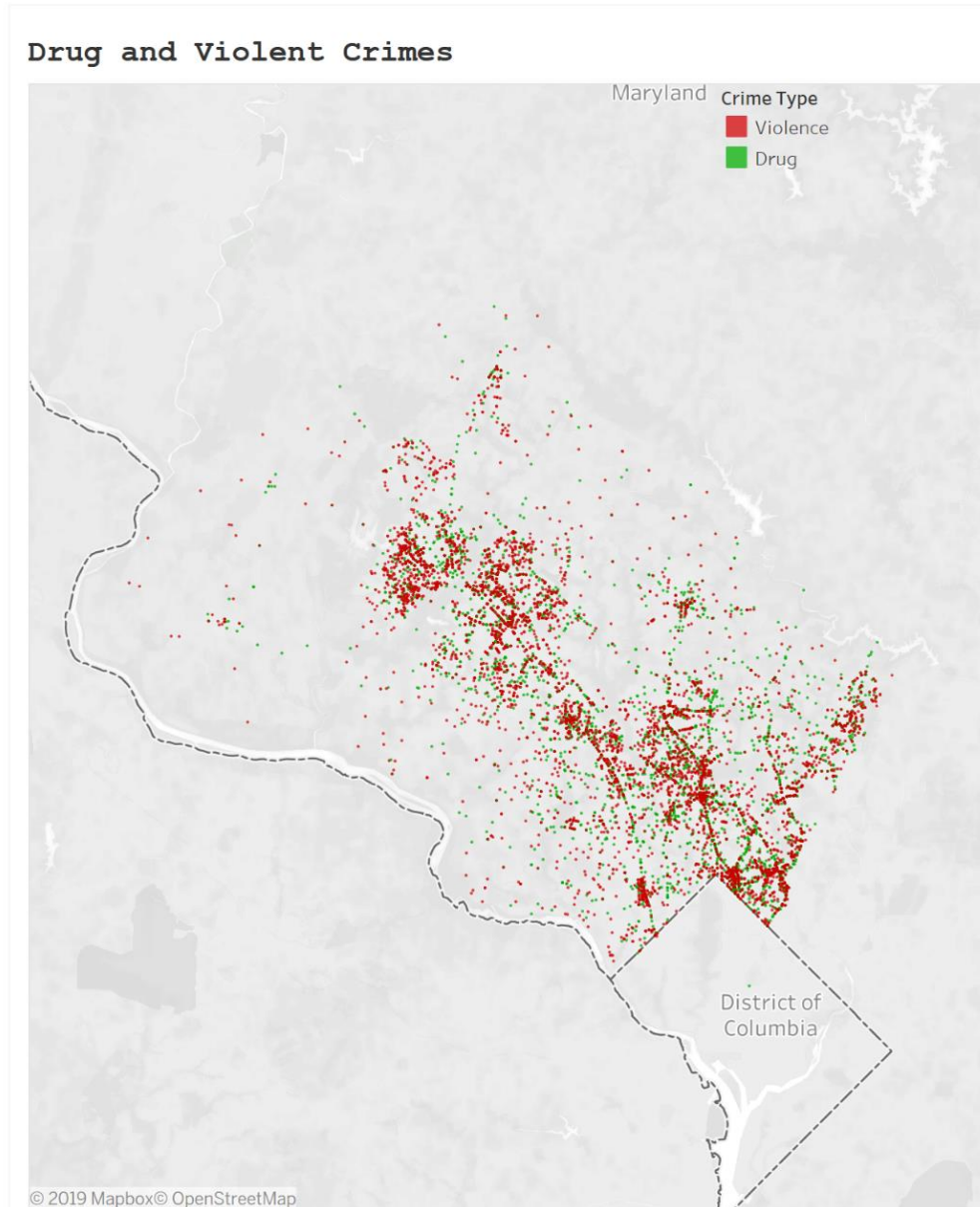
Ultimately it is important to always take into consideration the pros and cons of using Tableau Public instead of R. In this situation, even though I think the Tableau Public rendering is slicker, R did a better job getting the message across that there is a big difference in the location of drug-related crimes compared to violence-related crimes. It's also nice that the latitudes and longitudes are displayed automatically in R.

3. Bias Incidents:

The descriptive statistics for the variables used in the analysis are below.

Bias Incidents:	N	%
1. Incident		
Assault	56	17.02%
Intimidation	111	33.74%
Vandalism	129	39.21%
Other	33	10.03%
2. Victim Type		
Person	182	55.32%
Other	147	44.68%
3. District		
1D Rockville	53	18.73%
2D Bethesda	70	24.73%
3D Silver Spring	36	12.78%
4D Wheaton	54	19.08%
5D Germantown	36	12.78%
6D Gaithersburg	34	12.01%

Vandalism is the most common type of bias incident (39.21%) in this data. People were more often (55.32%) than "other" (e.g., schools, churches, offices, communities) to be the victims of bias incidents. The district with the highest number of bias incidents was surprisingly 2D Bethesda (24.73%). Already the descriptive statistics are interesting for this dataset. I would have never guessed Bethesda would be the place that has by far the highest number of bias incidents in Montgomery County considering it is supposed to be very educated. It would be interesting to know if the people that are apprehended committing these crimes are from outside Bethesda. This could be a good column to add to this dataset. It could be that Bethesda is used as a platform for prejudice and bigotry by people from other places. It could also be that it is a very homogeneous area that resists change. Without more data it is hard to know for sure why Bethesda has the highest number of reported bias incidents, especially, as we saw in the first two analyses, if we take into consideration the fact that Bethesda had some of the lowest numbers of traffic violations and crime.
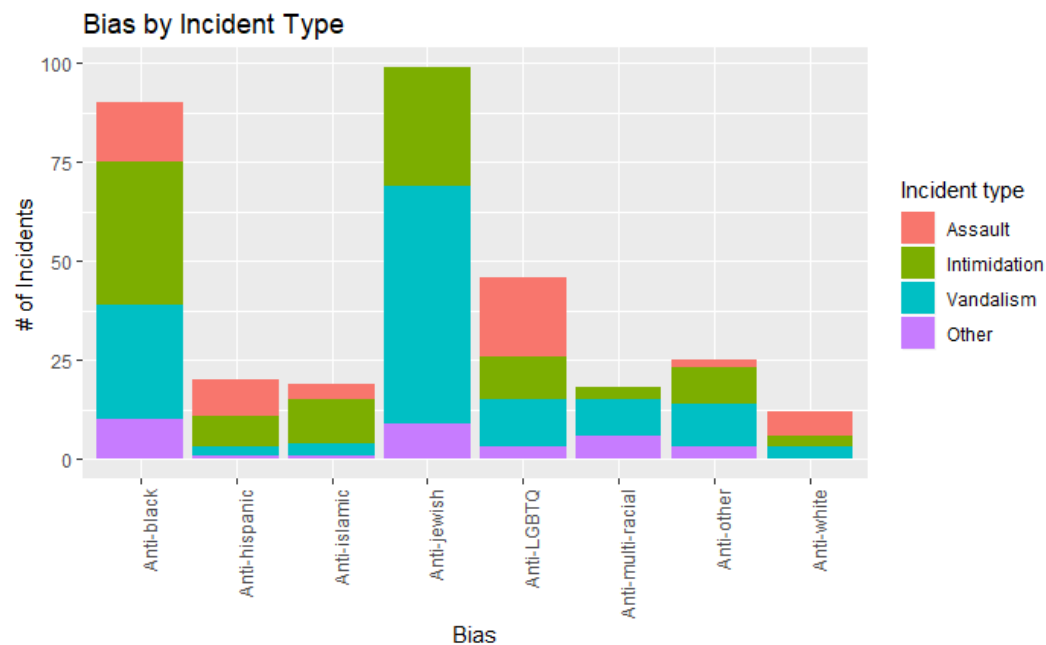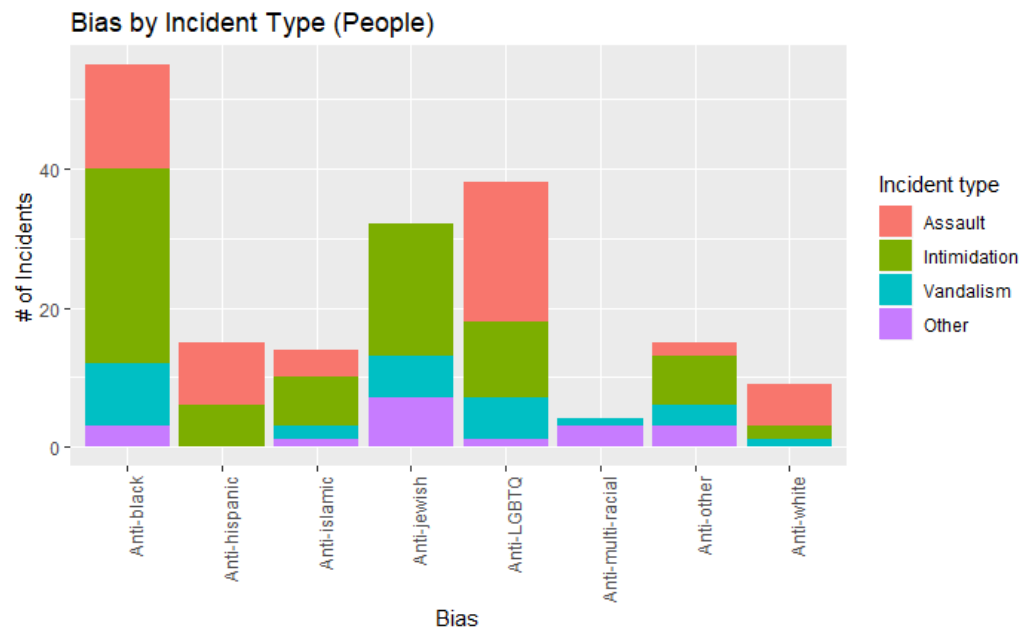
Figure 6.

Figure 7.

Bias by Incident Type (People)

One of the interesting findings of the present analysis is discerned from Figures 6 and 7. As can be seen in these two figures above, there is discord in the distribution of number of bias incidents and the type of bias when we filter for bias incidents committed against people. If we observe the overall distribution in Figure 6, at first glance it appears that anti-Jewish bias incidents numbers are alarming. When the bias incidents are broken down by incident type, we start to get a glimpse of the real picture; more than half of the anti-Jewish bias incidents are vandalisms. While vandalisms and intimidation are grave in their own way, assaults are much more important because they actually physically harm the victims. Physical harm has both physical and mental (potentially cognitive as well if a concussion is sustained) consequences while intimidation and vandalism only tend to affect the psyche. In the present data, no anti-Jewish bias incidents were assaults. Conversely, anti-LGBTQ bias incidents were rarely vandalisms and were mostly assaults and intimidation. When we break down the data to only viewing the bias incidents against people (Figure 7), we see that a whopping more than half of anti-LGBTQ bias incidents were assaults. We also observe that anti-black incidents are the most common when the victim is a person.

None of these types of incidents and types of biases are acceptable in our society in my opinion. It's very sad to see that after more than 400 years black people are still subject to bigotry, prejudice, and bias. The staggering number of anti-Jewish and anti-LGBTQ bias in this part of the world is also mind-boggling. I would have never expected to come to these conclusions analyzing data from Montgomery County but here we are. The important thing is that I (and others who come to the same conclusions) am aware now that the same social issues that plagued societies in previous centuries still exist. It's interesting that the media is more adamant about exterminating diseases like the Measles than exterminating bias incidents even though there are less Measles cases than there are bias incidents. Let's hope that more light is shed on this topic so that we may start the healing process.