Prosecution Project Team 4 Final Report

Daniel Cirkovic, Yi Jing, Samantha Thompson, & Xuemeng Wang

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0.1.1 Introduction

The Prosecution Project (tPP) is a collection of data that specifically investigates patterns in political violence and terrorism occurring in the United States from 1990 to the present. Data is continuously being added, so updates to the following analysis may need to occur when more recent data becomes available. Our analysis focuses on characteristics of the terrorists, and their acts, including demographics, religion, prosecution types, ideology, tactic, targeting, and group affiliation. Our goal is to show visually and statistically analyze how these variables change over time.

0.1.2 Methodology

In order to more clearly detect variable changes, we split the data into time periods separated by major terrorist events. We decided to take this approach to not just evenly split the entire time period (events are not evenly spaced, but amount of data included in each period is fairly similar), but to also see if these major events induced any specific patterns within the variables. We try to depict the reasoning behind these changes, but all of this is subjective - correlation is not necessary causation. The only conclusions we can draw for certain, come from the statistical tests performed, relating to the overall change of each variables' categories over time.

Some of the variables included many categories; and in order to fit them all into one graph, with enough data available within each category per period, we only took the categories with the highest frequencies - while combining some categories together. This was done on a case by case basis, and more information on how this was completed is in the Appendix. NA's for that variable were deleted only for that variable, making sure to leave the data in the complete data set in case there were values (not NA) for the other variables.

In order to find differences in each variable over time, we summed each category within the variable and time period, and divided it over the total amount per time period. This gives us the frequency of each category per period, so that we can test if it has differences over time.

The tests we used for this are the Pearson Chi-Square Test, Fisher Exact Test, and Cramer's V Statistics. Because of the minimal amount of data in some categories per time period, the Fisher Exact Test is included because it has more relaxed rules on data size, contrary to the Pearson Chi-Square Test which is testing similar things. Cramer's V is a little bit different in that it measures how important the period is in determining each categories count.

These tests do not tell us if the variables' categories are increasing or decreasing over time, so we created bar charts where all bars are equal to 100%, and within each period the categories are split into percentages.

We additionally wanted to see if any of the variables impacted the counts of another variable over time. To do this, we selected racial/ethnic group to compare with time against (1) prison sentence length, (2) plea and (3) tactic. The Cochran-Mantel Haenszel test was used in order to test the differences over time with now two variables and time, whereas we only had one with time in all previous tests.

0.1.3 Conclusion

We saw that characteristics of terrorists and their acts of terrorism have significant changes over the time period the data was collected in as of now. By using both visualizations and statistical tests, these changes can be closer investigated by importance and size, as each variable has its differences. Overall, the key variables to assign the most importance to based on the statistical tests are Othered Status, Citizenship, Tactic, and Group Affiliation. This is why the visualizations included in this report are chosen, and explored/researched reasons for these changes along with the directions of their differences.

0.2 Technical Report

0.2.1 Introduction

Terrorism in the United States peaked in the late 1960's and early 1970's, followed by a precipitous decline (Ross et al, 1989). Despite this decline, terrorism seems ever more present. Large scale media coverage and the development of social media have often been cited as contributors to discerned prevalence of terrorism (Weimann et al, 2014). Further, media coverage of events such as 9/11 has framed many attacks as "Muslims/Arabs/Islam working together in organized terrorist cells against a Christian America". On the other hand, domestic terrorists often receive the label of "troubled individuals" (Powell, 2011). Thus, there is strong evidence of media coverage affecting the perception of terrorist attacks in the United States. Given the Prosecution Project (tPP) dataset, trends in terrorist activity are analyzed by grouping events into periods delineated by large scale media events and detecting any changes between said periods. This organization of events may allow for the detection of changes in terrorism, perhaps due to perpetrators attempting to imitate previous attacks covered in the media.

0.2.2 Methodology

In order to recognize the patterns in demographics, prosecution types, ideology, tactic, targeting, sentence length, informant, and group affiliation over time, each event was organized into different time periods separated by major terrorist attacks in the United States. The events of interest are listed below:

Date	Event	Description	Period Number (After/Before Event)
04/19/1995	Oklahoma City Bombing	168 killed in terrorist attacking responding to standoff at Waco seige (1993).	1 (Before) 2 (After)
04/20/1999	Columbine School Shooting	13 killed by two gunmen, speculated to be a response to bullying.	3 (After)
09/11/2001	9/11	Series of four coordinated attacks perpetrated by al-Qaeda in response to US foreign policy.	4 (After)
03/25/2006	Capitol Hill Massacre	Kyle Aaron Huff entered a rave afterparty in the southeast part of Seattle's Capitol Hill neighborhood and opened fire, killing six and wounding two.	5 (After)

Date	Event	Description	Period Number (After/Before Event)
11/05/2009	Fort Hood Shooting	Nidal Malik Hasan, a US Army Major serving as a Psychiatrist, opens fire at Fort Hood, Texas, killing 13 and wounding 29.	6 (After)
02/26/2012	Death of Trayvon Martin	17 year-old African American shot by Afro-Peruvian man; racial profiling suspected.	7 (After)
12/14/2012	Sandy Hook School Shooting	27 people shot and killed, motive of killer unknown.	8 (After)
06/17/2015	Charleston Church Shooting	White man kills nine African Americans during church service; racially motivated.	9 (After)
07/07/2015	Aurora Theater Shooting	12 killed in movie theater, no political or racial motivation.	10 (After)
06/12/2016	Orlando Nightclub Shooting	49 people killed in response to death of ISIL leader; likely a consequence of homophobia.	11 (After)
02/14/2018	Parkland School Shooting	Gunman kills 17 students, motive unknown.	12 (After)

The purpose of this delineation is to determine whether these events, largely covered in the media, trigger "copycat" terrorist attacks (known as contagion) or somehow impact a variable's distribution in time periods near said events (Nacos, 2010).

Once each event was grouped, the frequencies of each variable category were computed within each time period and compared using 2-way contingency tables. That is, each variable had its own contingency table with the rows representing the categories given in the variable of interest, and the columns representing the time periods described earlier. Often, multiple categories were either condensed or removed due to sparseness of information (see Appendix for the exact breakdown of tables). The difference in distribution of the categories across time will be tested using both a Pearson Chi-Square Test and Fisher Exact Test.

The Pearson Chi-Square Contingency Table Test tests homogeneity of the time periods. More specifically, it decides whether or not there is a difference between the proportions of the categories of a certain variable across the time periods. For example, if the gender variable were to be considered, it would test whether the proportion of events committed by males and females has changed over time. However, it does not indicate the direction of these changes (Lachin, 2011).

Most of the variables, however, violate the expected count assumption of the Pearson Test. The test assumes that the expected counts in each of the cells are greater than five, but much of the tables contains zero values in multiple categories. Despite this violation, the Pearson Chi-Square Test is quite robust with these small expected cell frequencies (Camili, 163). To ensure this infraction does not impact results, an additional Fisher Exact Test is performed.

Fisher's Exact Test again tests a difference between time periods in each of the variable category proportions. Specifically, it counts the number of possible tables that could be constructed with the given marginal totals. Then, it computes the proportion of those tables that are more extreme than the observed table, giving a p-value (Raymond et al, 1995). Since this could amount to a large number of tables, a bootstrap simulation with 2000 replicates is considered. This test relaxes the assumptions given by the Pearson Chi-Square Test.

Trends will be visually analyzed using proportional, stacked bar charts. Along with the Pearson Chi-Square tests, Cramer's V statistics were computed. Cramer's V is a measure of association between two categorical values ranging from 0 to 1. The higher Cramer's V, the stronger the relationship between period and the given variable is (Acock et al, 1979).

Finally, the interaction between racial/ethnic group, prison sentence length, and time is considered. Perhaps, over time, certain races will have differing sentence lengths, whether that be a result of discrimination, ethnic tendencies, or other factors. A three dimensional table will be considered with a Cochran-Mantel Haenszel Test applied. This test is an extension of the Chi-Square Test, and, in general, tests for differences in the joint and marginal distributions of three variables (Lachin, 2011).

In each table, any unknown observations were not considered, since they add no information to the story, other that adding sample size and changing inference in a direction that may not necessarily be honest.

0.2.3 Results

From the collection of two-way tables, the distribution of most variables have changed over time. Only the distribution of death sentencing and gender seemed homogenous over time, as both the Fisher and Chi-Square tests failed to detect a difference in their distributions. The uniformity of gender and death sentencing throughout the periods is not surprising, as the vast majority of events in the dataset were perpetrated by men and did not result in a death sentencing of the perpetrator. More interesting insights can be gathered visually.

Variable	df	X^2 statistic	Cramer's V
Gender	11	11.8	0.089
Othered Status	11	229.43*	0.392
Ethnicity	44	329.14*	0.246
Religion	22	198.15*	0.259
Veteran Status	11	67.424*	0.223
Citizenship	11	145.24*	0.320

Variable	df	X^2 statistic	Cramer's V
Jurisdiction	11	100.47*	0.260
Plea	22	168.69*	0.242
Verdict	22	135.01*	0.213
Death Sentence	11	4.2269	0.068
Ideology	44	311.57*	0.292
Tactic	132	607.06*	0.283
Physical Target	44	192.98*	0.279
Ideological Target	44	391.61*	0.264
Informant	11	41.30*	0.167
Group Affiliation	110	1049.70*	0.322
FTO Affiliation	11	138.80*	0.306

* indicates statistical significance in both the Chi-Square and Fisher tests

All variables violated the Chi-Square assumption

The three-way tables invites some interesting insights. When comparing ethnicity, sentence length (categorized by every 100 months), and time period, there was no significant difference found between the distributions of the categories within each of the groups. The same results was reached when comparing ethnicity, plea, and time period. However, the Cochran-Mantel-Haenszel Test found a significant difference between the distribution of ethnicity and tactic over the time periods.

The following proportional, stacked bar charts show us how, and the direction of change, on the variables we felt were key to this analysis.

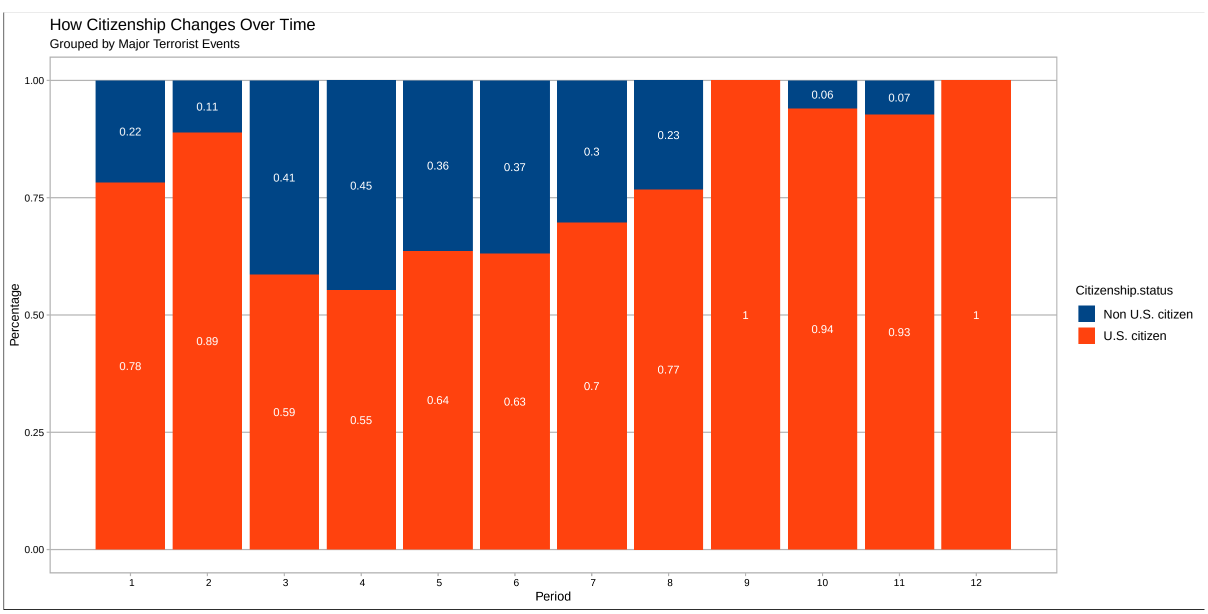

Figure 1: Stacked Bar Chart (1)

We see in *Figure 1* that the amount of terrorism acts by Non-U.S. citizens has consistently decreased over time, with it reaching very minimal counts by 2015 to present day. In 2011, the Department of Homeland Security defined a new term of "specially designated countries" to be countries "that have shown a tendency to promote, produce, or protect terrorist organizations or their members." In 2003, the Department of Homeland Security provided US border crossings with a list of 52 countries that fell under this term - in order to increase border security against possible terrorists. The list was continually updated and changed until present day. From 2007 to 2017, the US Border Patrol apprehended 45,006 immigrants from any of these countries to have ever been on the list. There have been zero attacks committed by illegal border crossings from any of the listed special designated countries. However, foreigners who have entered legally from these countries are responsible for 99.5% of all murders and 94.7% of all injuries committed by terrorists in the US from 1975 through the end of 2017 (Bier). We see that 9/11 may have spiked this trend that a successful strategy for foreign terrorism is to first enter legally, or to have a US citizen commit the act. After 9/11, the amount of non-US citizens to commit acts of terrorism is at its peak and then its decline. All terrorists involved in 9/11 were non-US citizens. This decrease in non-US citizens being able to commit acts of terrorism is likely the cause of increased security. However, terrorism is evolving so that the US may no longer be looking for non-US citizens to be committing these acts, as our graph shows.

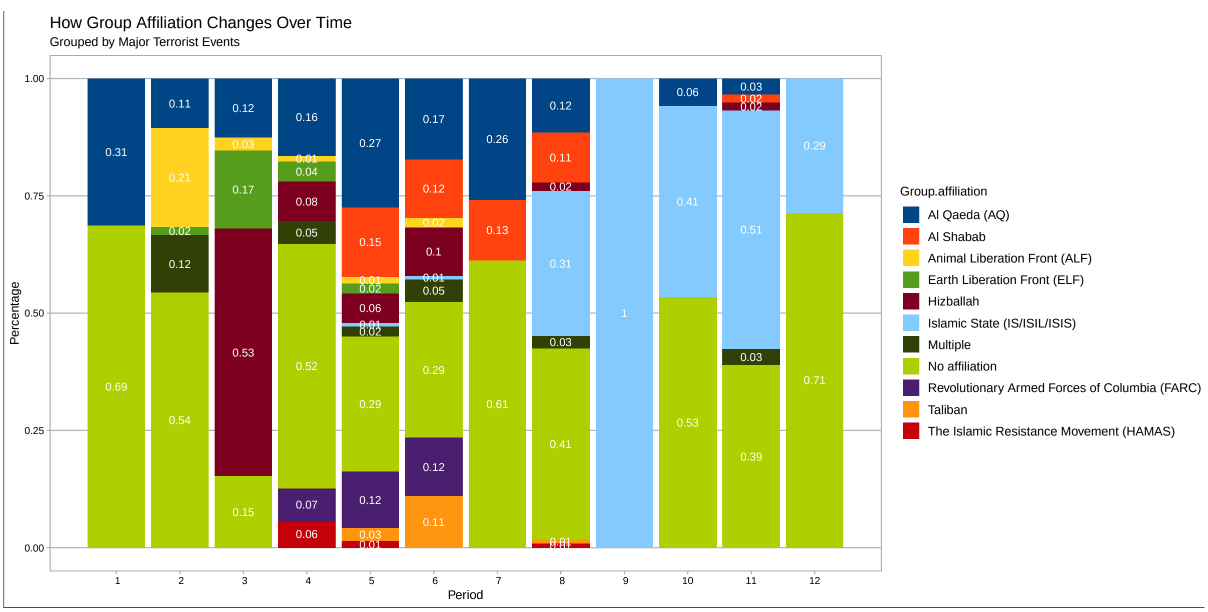

Figure 2: Stacked Bar Chart (2)

Figure 2 is very interesting in how group affiliation overall changes over time. Not looking into specific terrorist events, but at each group over time, we see that Al Qaeda has decreased consistently over time, but the Islamic State has increased - by large amounts especially in more recent years. There are many factors that play into this variable's directional changes, and we will try to summarize what we think is the cause the best that we can. Bin Laden, the previous leader of Al Qaeda, was killed in 2011. Period 6 is after the year 2009, and the period that we first start to see the decrease of Al Qaeda. This may be due to their leader dying, but some additional cause of conflict between groups could also play a role. Let's start at the beginning. Period 4 is after 9/11, an event Al Qaeda wished to take credit for, and therefore Al Qaeda is strong and on the rise here. In period 5, which is after 2006 when Al Shabab was formed, we see a heavier Al Shabab presence seen. Al Shabab was known to be tied to Al Qaeda, and they declared official allegiance to them in 2012. We see both Al Qaeda and Al Shabab decrease after period 8 (2012), which is what we would expect as Al Qaeda was weakened, so was Al Shabab because of their affiliation. We now start to see the rise of ISIS, who have taken advantage of the weakened Al Qaeda and Al Shabab, in order to make their presence more known. Although these groups have similar views, they are not supportive of one another, and have different tactics on how they wish to be heard. We can see how the changes in tactic over time graph below reflects these different groups, by which tactic they decided to use.

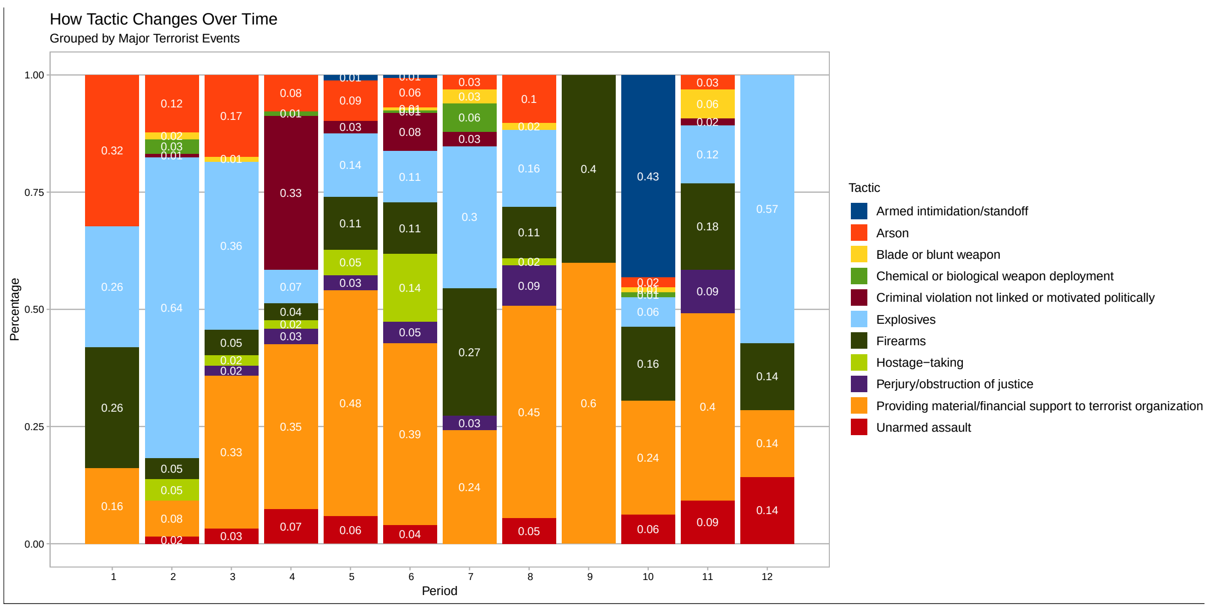

Figure 3: Stacked Bar Chart (3)

Going back on what we discuss in the previous paragraph, we can see in *Figure 3* that when Al Qaeda was in greater power, the categories of tactic that are most prevalent are crimes like Arson, Chemical or biological weapon deployment, and Explosives. These are all tactics that support Al Qaeda's goal to plot terrorism spectaculars to electrify the Muslim world. Whereas, ISIS viewpoint is to aim to control territory and expand their ideology. This can be seen as why once ISIS are in more power, the popular tactics are Providing material/financial support to terrorist organizations, Firearms, and Armed intimidation/standoff - all ways to overtake, build their organization, and control.

Additionally, from *Figure 3*, we see rises in tactic that could be the result of the major acts of terrorism we split the periods by. Explosives seem to increase from period 1 to period 2, which is after the Oklahoma City Bombing. Also, after the Aurora Theater Shooting, there seems to be a drastic decrease in civilian firearms, while there is an increase in armed intimidation/standoff. On another note, we see perjury/obstruction of justice slowly appear and begin to increase from past to present. This could be the cause of laws changing over time, so as stricter laws are implemented, more people may be convicted.

Other notable changes where graphics are not included are listed here. The terrorists' religion shows changes over time like after the Charleston Church Shooting, no Christians committed acts of terrorism. This could be due to the shooting happening in a Christian church, making other Christians less likely to commit any crimes or act out. The Veteran Status changing over time plot shows that after 9/11, the amount of veterans that committed acts of terrorism decreased drastically - then fluctuating but never again reaching the amount of terrorism acts before 9/11. Another change we see around 9/11 occurs in the ideological affiliation. We see that after 9/11 there is a massive increase in No Affiliation ideologies. This could be because groups were trying to draw attention away from themselves after all the security measures put into place after 9/11. We also see a huge increase in Rightist ideologies after the Charleston Church Shooting. This is interesting to note because the man that committed this act of terrorism was a 21-year-old white supremacist, who most likely believed in a rightist ideology. After the death of Trayvon Martin, State jurisdiction for acts of terrorism increased largely, possibly due to the pressure on local police following this event. The increase in verdict of charged but not tried over time can be due to possible ongoing cases as we get closer to present day. After the first major act of terrorism, we see more informants coming forward to prevent terrorist events.

The three-way tables invites some interesting insights. When comparing ethnicity, sentence length (categorized by every 100 months), and time period, there was no significant difference found between the distributions of the categories within each of the groups. The same results were reached when comparing ethnicity, plea, and time period. However, the Cochran-Mantel-Haenszel Test found a significant difference between the distribution of ethnicity and tactic over the time periods.

Contrast	df	M^2
Ethnicity vs Sentence Length vs Time	16	20.206
Ethnicity vs Plea vs Time	8	13.094
Ethnicity vs Tactic vs Time	44	513.96*

* indicates statistical significance

To further inspect these differences, a stacked bar plot was developed. Ethnicity was limited to only the white and middle eastern groups, as they provided interesting insight. Over time, it seems that of crimes in the data set committed by people of middle eastern ethnicity, the proportion of those crimes that included providing financial support to terrorist organizations has increased drastically over each time period. This occurrence spawned right before the 9/11 attacks. Crimes perpetrated by white individuals in Period 2, post Oklahoma City Bombing, started to consist mainly of explosives, perhaps furthering the idea of similar "copycat" crimes being committed after large media coverage of terrorist attacks. Similarly, after the Aurora shooting, white criminals seemed to heavily gravitate towards armed intimidation to commit their crimes as well. Other ethnicity plots can be seen in the Appendix.

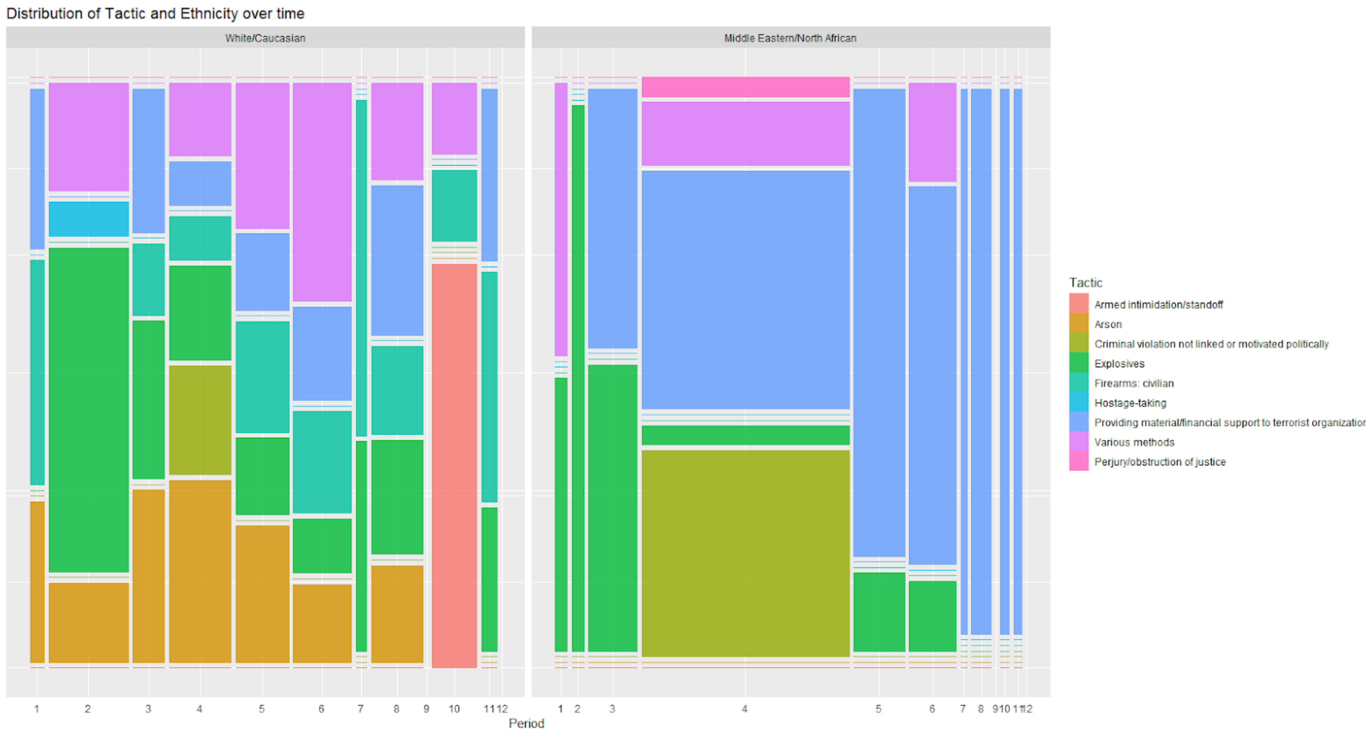

Figure 4: Mosaic Plot

0.2.4 Conclusion

The analysis provides some evidence that “copycat” terrorism or contagion impact the distribution of multiple characteristics of terrorist attacks over time. These changes are especially prevalent in the distribution of tactics across ethnicity and othered status after key events such as the Oklahoma City Bombing, 9/11, and the Aurora Shooting. Further, Ideological Affiliation trended towards Rightist Leanings after the Charleston Church Shooting, while Group Affiliation has seen a recent increase in attacks perpetrated by the Islamic State, despite the decrease in attacks perpetrated by Al-Qaeda. The claim that characteristics of these terrorist attacks are associated with the selected time periods are both bolstered by the results given by Chi-Square Tests and Cramer’s V quantitates. Of course, the Chi-Square Tests only say that period and terrorist attacks are associated and do not imply mechanism. However, the bar charts provide the context to our hypothesis. The analysis is limited by sparseness of events in some categories in which measures were taken to combat.

0.3 References

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0.4 Appendix

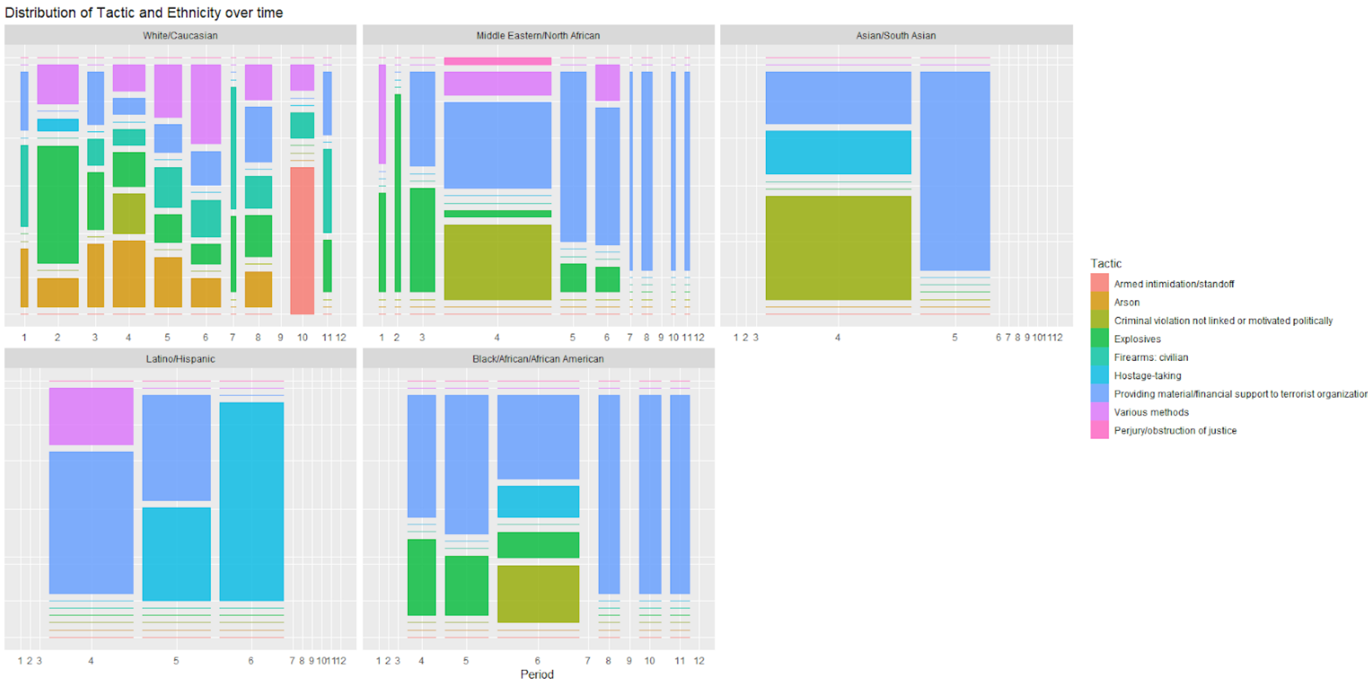


Figure 5: Ethnicity Plots

0.4.1 Tables

The collection of two dimensional contingency tables used in the analysis are provided. Note, categories have been condensed from the original data set. Cells are given in the following format:

Table 4: Age

	Period
Category	Frequency; Column Proportion

Table 5: Gender

Minimum	1st Quartile	Median	3rd Quartile	Maximum	Mean
16 yrs	25 yrs	33 yrs	44 yrs	88 yrs	35.75 yrs

Table 6: Othered Status

	1	2	3	4	5	6	7	8	9	10	11	12
Female	5; 0.1	9; 0.06	9; 0.1	35; 0.08	9; 0.05	13; 0.06	3; 0.07	17; 0.13	0; 0	9; 0.08	4; 0.06	0; 0
Male	46; 0.9	145; 0.94	85; 0.9	401; 0.92	183; 0.95	191; 0.94	39; 0.93	111; 0.87	6; 1	98; 0.92	62; 0.94	8; 1

Table 7: Ethnicity

	1	2	3	4	5	6	7	8	9	10	11	12
Non-othered	25; 0.49	134; 0.87	47; 0.5	93; 0.21	68; 0.35	70; 0.34	21; 0.5	58; 0.45	2; 0.33	61; 0.56	25; 0.38	3; 0.38
Othered	26; 0.51	20; 0.13	47; 0.5	343; 0.79	124; 0.65	135; 0.66	21; 0.5	70; 0.55	4; 0.67	47; 0.44	41; 0.62	5; 0.62

Table 8: Religion

	1	2	3	4	5	6	7	8	9	10	11	12
Asian/South Asian	0; 0	1; 0.01	0; 0	36; 0.1	13; 0.07	3; 0.02	2; 0.05	7; 0.06	0; 0	3; 0.03	1; 0.02	1; 0.14
Black/African/African American	9; 0.2	4; 0.03	2; 0.02	23; 0.06	24; 0.13	44; 0.22	6; 0.15	22; 0.17	2; 0.33	14; 0.14	17; 0.29	1; 0.14
Latino/Hispanic	2; 0.04	1; 0.01	1; 0.01	31; 0.09	17; 0.09	23; 0.12	1; 0.02	1; 0.01	0; 0	3; 0.03	1; 0.02	2; 0.29
Middle Eastern/North African	11; 0.24	14; 0.11	41; 0.46	183; 0.5	54; 0.29	41; 0.2	11; 0.27	24; 0.19	1; 0.17	14; 0.14	12; 0.2	1; 0.14
White/Caucasian	24; 0.52	111; 0.85	45; 0.51	91; 0.25	78; 0.42	89; 0.44	21; 0.51	72; 0.57	3; 0.5	63; 0.65	28; 0.47	2; 0.29

| |1|2|3|4|5|6|7|8|9|10|11|12| |——————|————|————|————|————|————|————|————|————|————|————|————|————|Christian|13; 0.25|24; 0.16|9; 0.1|6; 0.01|19; 0.1|18; 0.09|2; 0.05|15; 0.12|0; 0|36; 0.34|7; 0.11|1; 0.12| |Christian Identity|6; 0.12|20; 0.13|8; 0.09|6; 0.01|2; 0.01|5; 0.03|4; 0.1|3; 0.02|0; 0|0; 0|1; 0.02|0; 0| |Muslim|13; 0.25|17; 0.11|44; 0.47|187; 0.43|94; 0.49|91; 0.46|16; 0.38|66; 0.52|5; 0.83|41; 0.38|32; 0.48|2; 0.25| |Other|19; 0.37|89; 0.59|33; 0.35|234; 0.54|77; 0.4|82; 0.42|20; 0.48|43; 0.34|1; 0.17|30; 0.28|26; 0.39|5; 0.62|

Table 9: Veteran Status

	1	2	3	4	5	6	7	8	9	10	11	12
Veteran/Active Duty	4; 0.08	19; 0.14	27; 0.29	24; 0.06	22; 0.14	13; 0.07	7; 0.17	4; 0.03	0; 0	5; 0.06	12; 0.19	0; 0
Civilian	46; 0.92	113; 0.86	67; 0.71	383; 0.94	138; 0.86	167; 0.93	35; 0.83	117; 0.97	6; 1	83; 0.94	52; 0.81	8; 1

Table 10: Citizenship

	1	2	3	4	5	6	7	8	9	10	11	12
Foreign National	11; 0.28	13; 0.08	38; 0.41	169; 0.42	49; 0.26	66; 0.33	11; 0.26	19; 0.15	0; 0	4; 0.04	3; 0.05	0; 0
Citizen	28; 0.72	141; 0.92	54; 0.59	231; 0.58	140; 0.74	135; 0.67	31; 0.74	106; 0.85	6; 1	96; 0.96	63; 0.95	8; 1

Table 11: Jurisdiction

	1	2	3	4	5	6	7	8	9	10	11	12
State	15; 0.29	19; 0.12	7; 0.07	13; 0.03	19; 0.1	18; 0.09	14; 0.33	14; 0.11	1; 0.17	25; 0.23	16; 0.24	2; 0.25
Federal	36; 0.71	134; 0.88	87; 0.93	421; 0.97	173; 0.9	187; 0.91	28; 0.67	114; 0.89	5; 0.83	83; 0.77	50; 0.76	6; 0.75

Table 12: Plea

	1	2	3	4	5	6	7	8	9	10	11	12
Charged	9; 0.19	2; 0.01	24; 0.26	43; 0.1	22; 0.12	39; 0.2	1; 0.03	6; 0.05	0; 0	21; 0.2	16; 0.25	4; 0.5
Not Guilty	17; 0.36	83; 0.54	19; 0.2	110; 0.26	56; 0.3	16; 0.08	12; 0.32	23; 0.19	2; 0.33	27; 0.25	11; 0.17	0; 0
Guilty	21; 0.45	69; 0.45	51; 0.54	275; 0.64	109; 0.58	136; 0.71	25; 0.66	92; 0.76	4; 0.67	58; 0.55	37; 0.58	4; 0.5

Table 13: Verdict

	1	2	3	4	5	6	7	8	9	10	11	12
Charged	9; 0.18	3; 0.02	24; 0.26	47; 0.11	22; 0.11	40; 0.2	4; 0.1	19; 0.15	0; 0	25; 0.24	30; 0.46	4; 0.5

	1	2	3	4	5	6	7	8	9	10	11	12
Guilty	42; 0.82	138; 0.9	69; 0.73	381; 0.88	167; 0.87	156; 0.76	37; 0.9	106; 0.84	6; 1	75; 0.71	34; 0.52	4; 0.5
Not Guilty	0; 0	13; 0.08	1; 0.01	7; 0.02	3; 0.02	8; 0.04	0; 0	1; 0.01	0; 0	6; 0.06	1; 0.02	0; 0

Table 14: Length of Sentence

Minimum	1st Quartile	Median	3rd Quartile	Maximum	Mean
0.0 mths	12.0 mths	60.0 mths	168.0 mths	4816.0 mths	113.1 mths

Table 15: Death Sentence

	1	2	3	4	5	6	7	8	9	10	11	12
No	24; 1	97; 1	48; 1	292; 0.99	128; 1	126; 1	27; 1	86; 1	5; 1	50; 1	27; 1	2; 1
Yes	0; 0	0; 0	0; 0	2; 0.01	0; 0	0; 0	0; 0	0; 0	0; 0	0; 0	0; 0	0; 0

Table 16: Ideology

	1	2	3	4	5	6	7	8	9	10	11	12
Leftist	1; 0.04	14; 0.14	13; 0.27	43; 0.15	21; 0.16	4; 0.03	7; 0.26	6; 0.07	0; 0	2; 0.04	3; 0.11	0; 0
Rightist	16; 0.67	73; 0.75	14; 0.29	39; 0.13	37; 0.29	37; 0.29	7; 0.26	31; 0.36	1; 0.2	18; 0.36	3; 0.11	1; 0.5
Other	2; 0.08	1; 0.01	3; 0.06	98; 0.33	4; 0.03	19; 0.15	2; 0.07	7; 0.08	0; 0	1; 0.02	5; 0.19	0; 0
Nationalist-Separatist	1; 0.04	0; 0	6; 0.12	12; 0.04	3; 0.02	2; 0.02	0; 0	1; 0.01	0; 0	1; 0.02	0; 0	0; 0
Salafi/Jihadist/Islamist	4; 0.17	9; 0.09	12; 0.25	102; 0.35	63; 0.49	64; 0.51	11; 0.41	41; 0.48	4; 0.8	28; 0.56	16; 0.59	1; 0.5

Table 17: Tactic

	1	2	3	4	5	6	7	8	9	10	11	12
Providing material/financial support to terrorist organization	5; 0.1	10; 0.06	30; 0.32	134; 0.32	80; 0.4	63; 0.28	8; 0.19	47; 0.37	3; 0.5	23; 0.22	24; 0.39	1; 0.14
Explosives	9; 0.18	84; 0.53	33; 0.35	28; 0.07	24; 0.12	18; 0.08	19; 0.21	18; 0.14	0; 0	6; 0.06	8; 0.13	4; 0.57
Various methods	7; 0.14	22; 0.14	2; 0.02	48; 0.12	21; 0.11	38; 0.17	10; 0.24	16; 0.13	1; 0.17	13; 0.13	2; 0.03	1; 0.14
Arson	13; 0.27	16; 0.1	16; 0.17	30; 0.07	16; 0.08	11; 0.05	1; 0.02	12; 0.09	0; 0	2; 0.02	2; 0.03	0; 0
Firearms: civilian	12; 0.24	4; 0.03	5; 0.05	9; 0.02	18; 0.09	15; 0.07	9; 0.21	13; 0.1	2; 0.33	13; 0.13	11; 0.18	1; 0.14
Hostage-taking	1; 0.02	6; 0.04	2; 0.02	7; 0.02	10; 0.05	25; 0.11	0; 0	2; 0.02	0; 0	0; 0	0; 0	0; 0
Perjury/obstruction of justice	0; 0	0; 0	2; 0.02	12; 0.03	3; 0.02	7; 0.03	1; 0.02	9; 0.07	0; 0	0; 0	6; 0.1	0; 0
Armed intimidation/standoff	1; 0.02	0; 0	0; 0	0; 0	2; 0.01	1; 0	0; 0	0; 0	0; 0	41; 0.4	0; 0	0; 0
Firearms: military	0; 0	1; 0.01	0; 0	4; 0.01	1; 0.01	3; 0.01	0; 0	2; 0.02	0; 0	1; 0.01	1; 0.02	0; 0
Blade or blunt weapon	0; 0	2; 0.01	1; 0.01	0; 0	0; 0	1; 0	1; 0.02	2; 0.02	0; 0	1; 0.01	4; 0.07	0; 0
Chemical or biological weapon deployment	0; 0	4; 0.03	0; 0	4; 0.01	0; 0	1; 0	2; 0.05	0; 0	0; 0	1; 0.01	0; 0	0; 0

	1	2	3	4	5	6	7	8	9	10	11	12
Criminal violation not linked or motivated politically	0; 0	1; 0.01	0; 0	126; 0.3	5; 0.03	14; 0.06	1; 0.02	0; 0	0; 0	0; 0	1; 0.02	0; 0
Unarmed Assault	1; 0.02	8; 0.05	4; 0.04	12; 0.03	18; 0.09	27; 0.12	0; 0	6; 0.05	0; 0	2; 0.02	2; 0.03	0; 0

Table 18: Physical Target

	1	2	3	4	5	6	7	8	9	10	11	12
Public	18; 0.44	13; 0.11	5; 0.09	22; 0.22	15; 0.21	13; 0.16	4; 0.15	12; 0.3	1; 0.5	38; 0.58	9; 0.41	2; 0.5
Federal	9; 0.22	43; 0.38	21; 0.38	12; 0.12	20; 0.28	20; 0.25	10; 0.38	14; 0.35	0; 0	7; 0.11	3; 0.14	1; 0.25
State	3; 0.07	23; 0.2	3; 0.05	20; 0.2	13; 0.18	15; 0.19	5; 0.19	8; 0.2	0; 0	3; 0.05	7; 0.32	1; 0.25
Mass Transportation	2; 0.05	3; 0.03	7; 0.13	8; 0.08	7; 0.1	25; 0.31	6; 0.23	1; 0.02	0; 0	0; 0	3; 0.14	0; 0
Private	9; 0.22	32; 0.28	19; 0.35	37; 0.37	17; 0.24	8; 0.1	1; 0.04	5; 0.12	1; 0.5	18; 0.27	0; 0	0; 0

Table 19: Ideological Target

	1	2	3	4	5	6	7	8	9	10	11	12
Public	1; 0.02	23; 0.16	32; 0.38	301; 0.72	89; 0.49	99; 0.53	15; 0.38	62; 0.51	4; 1	28; 0.27	40; 0.65	4; 0.57
Government	15; 0.32	81; 0.55	28; 0.33	56; 0.13	53; 0.29	65; 0.35	14; 0.35	26; 0.21	0; 0	40; 0.38	5; 0.08	1; 0.14
Identity	7; 0.15	11; 0.08	4; 0.05	16; 0.04	12; 0.07	11; 0.06	6; 0.15	13; 0.11	0; 0	22; 0.21	10; 0.16	1; 0.14
Industry	12; 0.26	28; 0.19	20; 0.24	39; 0.09	19; 0.1	6; 0.03	4; 0.1	7; 0.06	0; 0	4; 0.04	4; 0.06	0; 0
Religious	12; 0.26	3; 0.02	1; 0.01	5; 0.01	8; 0.04	6; 0.03	1; 0.02	13; 0.11	0; 0	10; 0.1	3; 0.05	1; 0.14

Table 20: Informant

	1	2	3	4	5	6	7	8	9	10	11	12
No	45; 0.88	80; 0.52	61; 0.65	293; 0.67	123; 0.65	114; 0.58	23; 0.57	79; 0.62	2; 0.33	52; 0.48	44; 0.68	5; 0.62
Yes	6; 0.12	74; 0.48	33; 0.35	142; 0.33	66; 0.35	82; 0.42	17; 0.42	48; 0.38	4; 0.67	56; 0.52	21; 0.32	3; 0.38

Table 21: Group Affiliation

	1	2	3	4	5	6	7	8	9	10	11	12
Al Qaeda (AQ)	5; 0.24	6; 0.11	9; 0.12	57; 0.17	40; 0.31	22; 0.17	7; 0.25	11; 0.12	0; 0	3; 0.04	1; 0.02	0; 0
Al Shabab	0; 0	0; 0	0; 0	0; 0	20; 0.15	9; 0.07	3; 0.11	10; 0.11	0; 0	0; 0	1; 0.02	0; 0
Animal Liberation Front (ALF)	1; 0.05	12; 0.22	2; 0.03	4; 0.01	2; 0.02	3; 0.02	0; 0	0; 0	0; 0	0; 0	0; 0	0; 0
Earth Liberation Front (ELF)	0; 0	1; 0.02	12; 0.17	15; 0.04	3; 0.02	0; 0	0; 0	0; 0	0; 0	0; 0	0; 0	0; 0
Hizballah	0; 0	0; 0	38; 0.53	29; 0.09	4; 0.03	15; 0.12	0; 0	0; 0	0; 0	0; 0	1; 0.02	0; 0
Islamic State (IS/ISIL/ISIS)	0; 0	0; 0	0; 0	0; 0	0; 0	1; 0.01	0; 0	28; 0.3	5; 1	35; 0.43	27; 0.5	2; 0.29
Multiple	0; 0	7; 0.13	0; 0	17; 0.05	3; 0.02	7; 0.06	0; 0	3; 0.03	0; 0	0; 0	2; 0.04	0; 0
No affiliation	15; 0.71	29; 0.53	11; 0.15	172; 0.51	37; 0.28	36; 0.28	18; 0.64	40; 0.43	0; 0	44; 0.54	22; 0.41	5; 0.71
Revolutionary Armed Forces of Columbia (FARC)	0; 0	0; 0	0; 0	24; 0.07	17; 0.13	18; 0.14	0; 0	0; 0	0; 0	0; 0	0; 0	0; 0
Taliban	0; 0	0; 0	0; 0	0; 0	4; 0.03	16; 0.13	0; 0	1; 0.01	0; 0	0; 0	0; 0	0; 0

	1	2	3	4	5	6	7	8	9	10	11	12
The Islamic Resistance Movement (HAMAS)	0; 0	0; 0	0; 0	20; 0.06	1; 0.01	0; 0	0; 0	0; 0	0; 0	0; 0	0; 0	0; 0

Table 22: FTO Affiliation

	1	2	3	4	5	6	7	8	9	10	11	12
No	30; 0.59	144; 0.94	39; 0.41	237; 0.55	70; 0.37	101; 0.5	25; 0.6	65; 0.51	1; 0.17	65; 0.6	28; 0.43	6; 0.75
Yes	21; 0.41	10; 0.06	55; 0.59	194; 0.45	121; 0.63	103; 0.5	17; 0.4	63; 0.49	5; 0.83	43; 0.4	37; 0.57	2; 0.25

0.4.2 Stacked Bar Charts & Code

```
##############################################################################################
# tPP Stacked Bar Charts Code
# Author: Samantha Thompson (thomp153@miamioh.edu)
# Purpose: 1. Create Category Percentages within each Variable
#          2. Created Stacked Bar Chart Visualizations with Percentages for each Categ
##############################################################################################

# Read in dataset
pros <- read.csv(file="U__FOUO Spreadsheet - CLEAN.csv")

# Load necessary packages
library(lubridate)
```

```
##
## Attaching package: 'lubridate'

## The following object is masked from 'package:base':
##
##     date
```

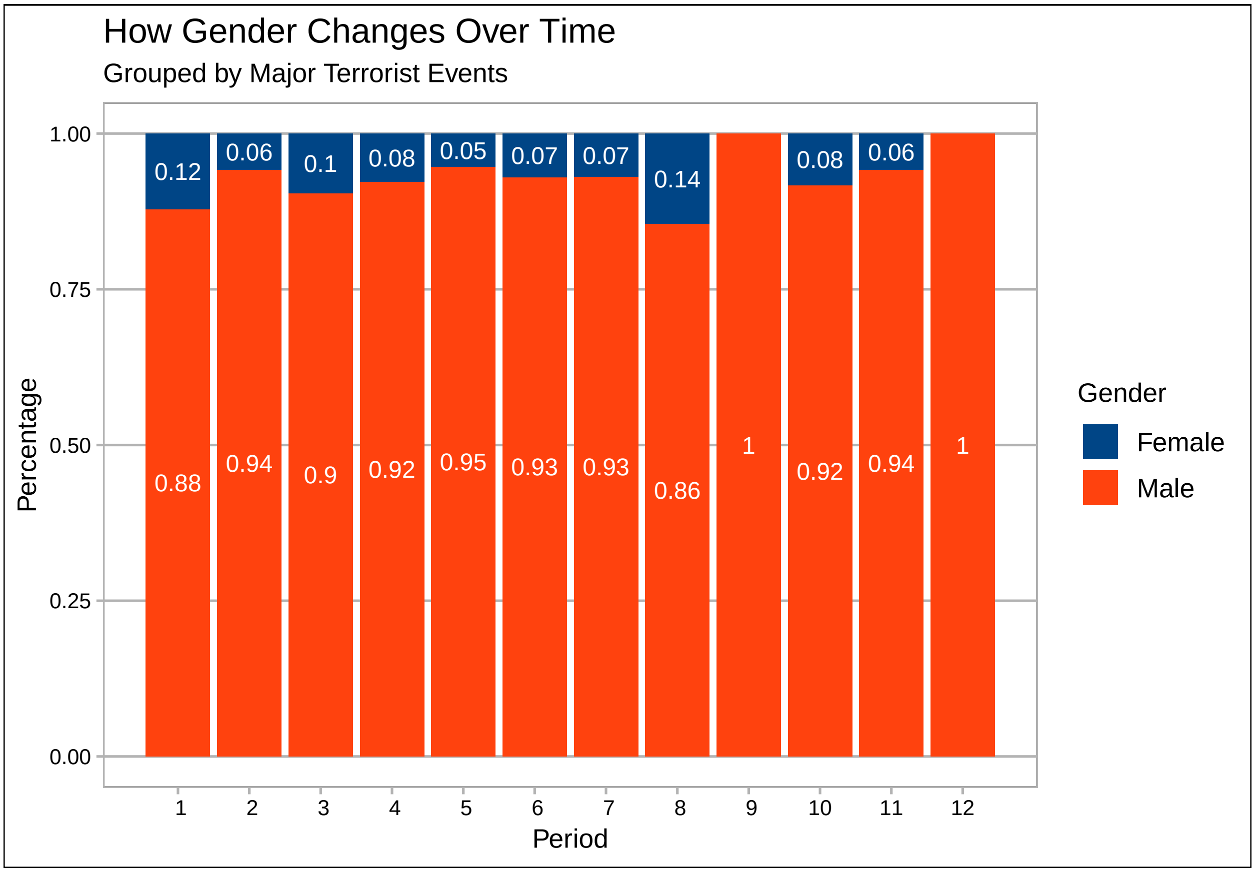
```
library(dplyr)
```

```
##
```

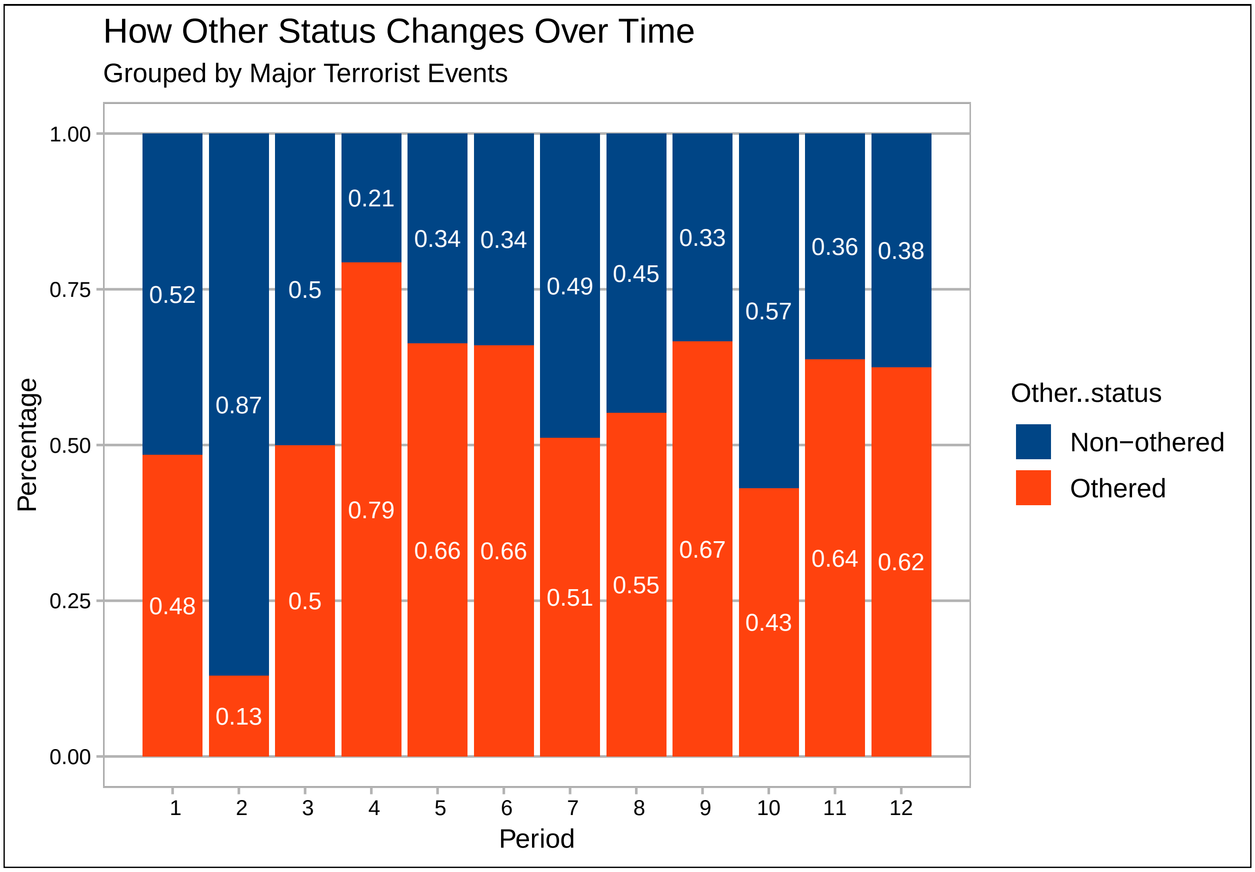
```
## Attaching package: 'dplyr'

## The following objects are masked from 'package:lubridate':
##
##     intersect, setdiff, union

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
library(ggplot2)
library(ggthemes)

# Put into date format
pros <- pros %>%
  mutate(Date = mdy(Date))

### Create new 'Period' variabe that separates events into one of the 12 periods where t
## Terrorism ##
# (1) Oklahoma City (Apr 19, 1995)
# (2) Columbine (Apr 20, 1999)
# (3) 9/11 (Sept 11, 2001)
# (4) Capitol Hill Massacre (March 25, 2006)
# (5) Fort Hood Shooting (November 5, 2009)
# (6) Trayvon Martin (Feb 26, 2012)
# (7) Sandy Hook (Dec 14, 2012)
# (8) Charleston (June 17, 2015)
# (9) Aurora (July 20, 2015)
# (10) Orlando Night Club (June 12, 2016)
# (11) Parkland School (Feb 14, 2018)

prosNEW <- pros %>%
  mutate(Period = ifelse(Date <= '1995-04-19', 1,
                  ifelse(Date > '1995-04-19' & Date <= '1999-04-20', 2,
                  ifelse(Date > '1999-04-20' & Date <= '2001-09-11', 3,
                  ifelse(Date > '2001-09-11' & Date <= '2006-03-25', 4,
                  ifelse(Date > '2006-03-25' & Date <= '2009-11-05', 5,
                  ifelse(Date > '2009-11-05' & Date <= '2012-02-26', 6,
                  ifelse(Date > '2012-02-26' & Date <= '2012-12-14', 7,
                  ifelse(Date > '2012-12-14' & Date <= '2015-06-17', 8,
                  ifelse(Date > '2015-06-17' & Date <= '2015-07-20', 9,
                  ifelse(Date > '2015-07-20' & Date <= '2016-06-12', 10,
```

```r
                  ifelse(Date > '2016-06-12' & Date <= '2018-02-14', 11, 12))))))))))))



### Aggregating variables for plots (creating percentages)

# Gender: Male and Female
attach(prosNEW)
# Delete these categories
test1 <- prosNEW[which(Gender!='Non-binary/gender non-conforming' &
                           Gender != 'Unknown/unclear'),]
# Only include M/F categories
test1 <- test1 %>%
  mutate(Gender = ifelse(Gender == "Female", "Female", "Male"))

gender.count <- test1 %>%
  dplyr::group_by(Gender, Period) %>%
  dplyr::summarise(n = n()) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::group_by(Period) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::mutate(freq = round(freq,digits=2))

ggplot(gender.count, aes(x=Period, y=n, fill=Gender)) +
  geom_bar(size=2, stat="identity", position="fill") +
  scale_x_discrete(name ="Period", limits=c(1:12)) +
  theme_minimal() +
  labs(y="Percentage", title="How Gender Changes Over Time",
       subtitle="Grouped by Major Terrorist Events") +
  geom_text(aes(label=freq),stat='identity',
            position=position_fill(vjust=0.5),color="white",size=3) +
  theme_calc() + scale_fill_calc()
```

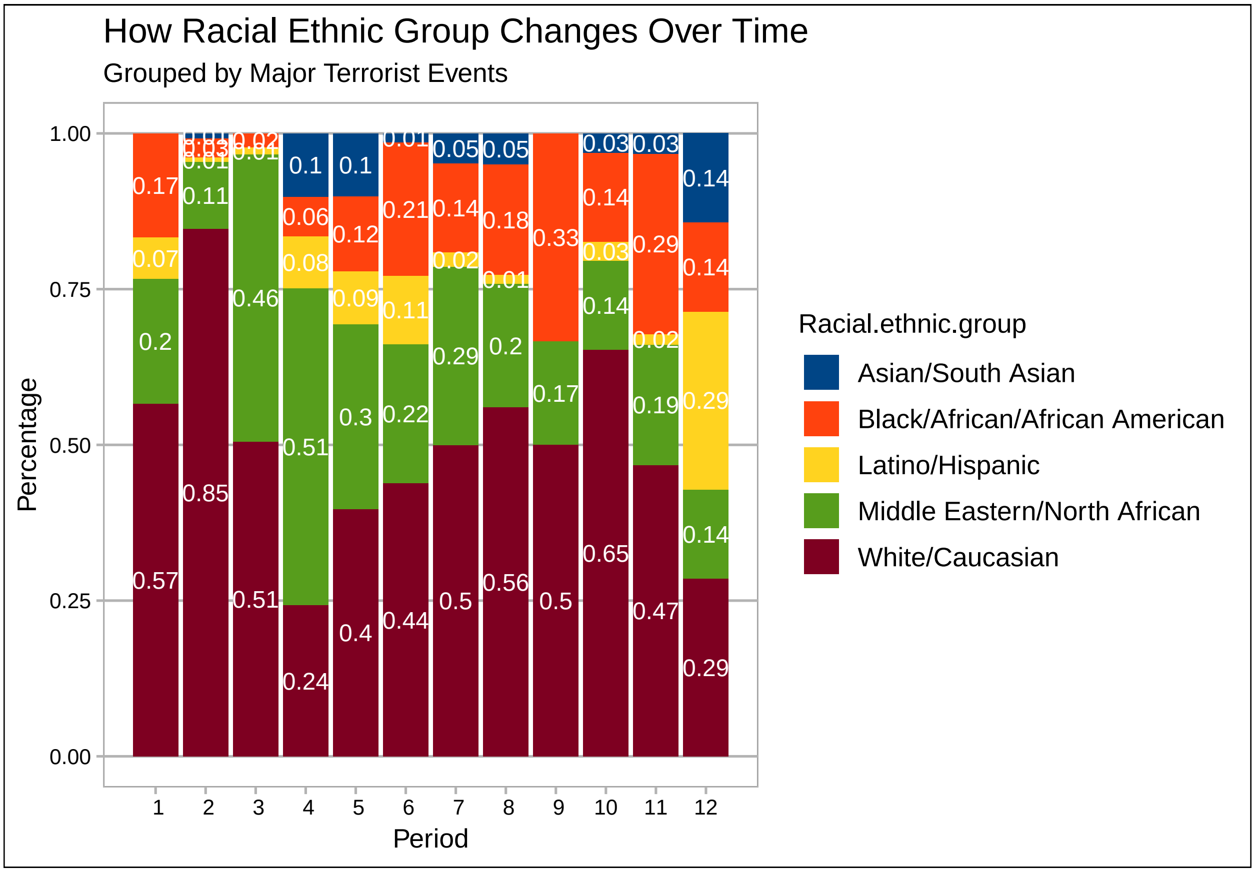



```r
# Other.Status: Othered and Non-othered
other.count <- prosNEW %>%
  dplyr::group_by(Other..status, Period) %>%
  dplyr::summarise(n = n()) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::group_by(Period) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::mutate(freq = round(freq,digits=2))

ggplot(other.count, aes(x=Period, y=n, fill=Other..status)) +
  geom_bar(size=2, stat="identity", position="fill") +
  scale_x_discrete(name ="Period", limits=c(1:12)) +
  theme_minimal() +
  labs(y="Percentage", title="How Other Status Changes Over Time",
       subtitle="Grouped by Major Terrorist Events") +
  geom_text(aes(label=freq),stat='identity',
            position=position_fill(vjust=0.5),color="white",size=3) +
  theme_calc() + scale_fill_calc()
```



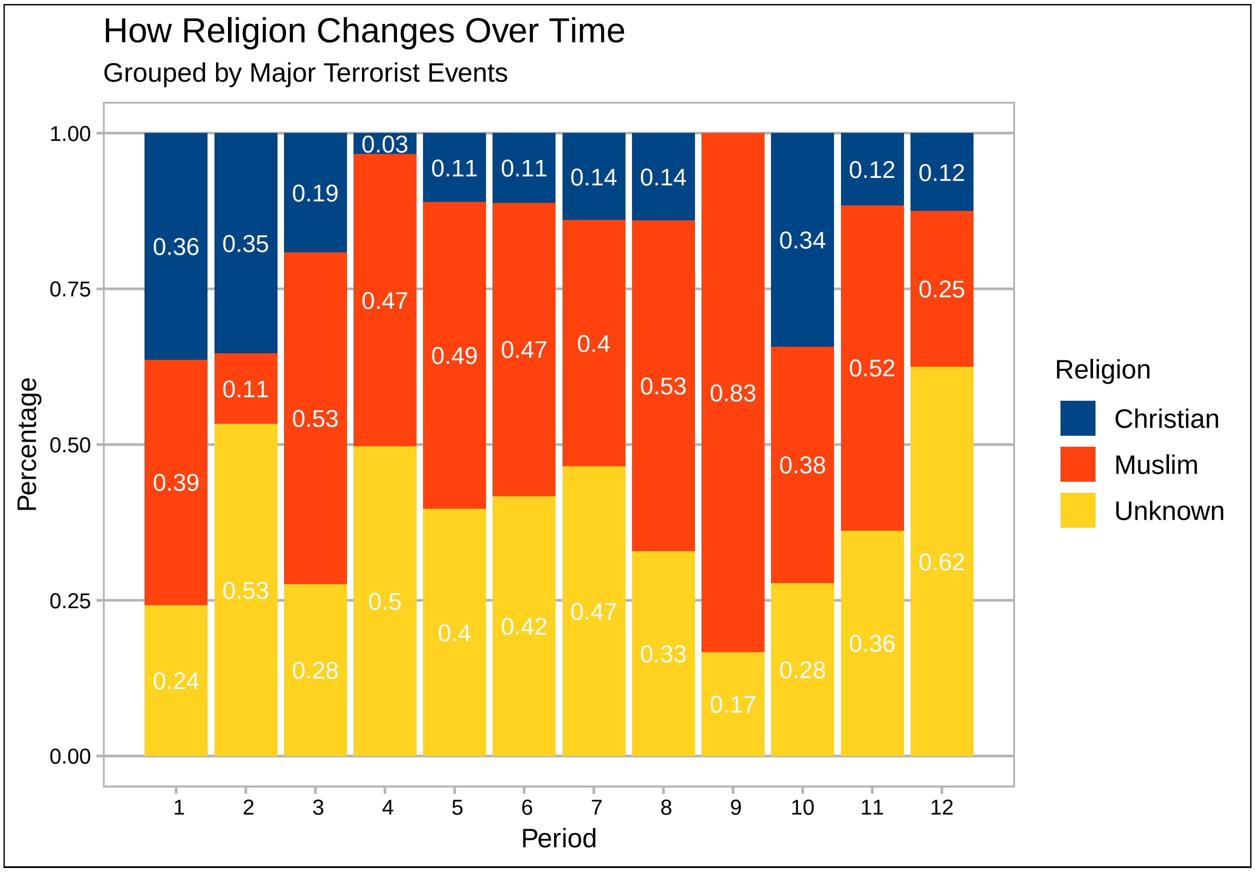

```
# Racial.Ethnic.Group: White/Caucasian, Middle Eastern/North African,
#                     Black/African/African American,
#                     Latino/Hispanic, Asian/South Asian
# Delete these categories
test2 <- prosNEW[which(Racial.ethnic.group != "Unknown" &
                         Racial.ethnic.group != "American Indian/Alaska Native" &
                         Racial.ethnic.group != "Biracial/Multiracial"),]

racial.count <- test2 %>%
  dplyr::group_by(Racial.ethnic.group, Period) %>%
  dplyr::summarise(n = n()) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::group_by(Period) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::mutate(freq = round(freq,digits=2))

ggplot(racial.count, aes(x=Period, y=n, fill=Racial.ethnic.group)) +
  geom_bar(size=2, stat="identity", position="fill") +
  scale_x_discrete(name ="Period", limits=c(1:12)) +
  theme_minimal() +
  labs(y="Percentage", title="How Racial Ethnic Group Changes Over Time",
```

```
       subtitle="Grouped by Major Terrorist Events") +
  geom_text(aes(label=freq),stat='identity',
            position=position_fill(vjust=0.5),color="white",size=3) +
  theme_calc() + scale_fill_calc()
```



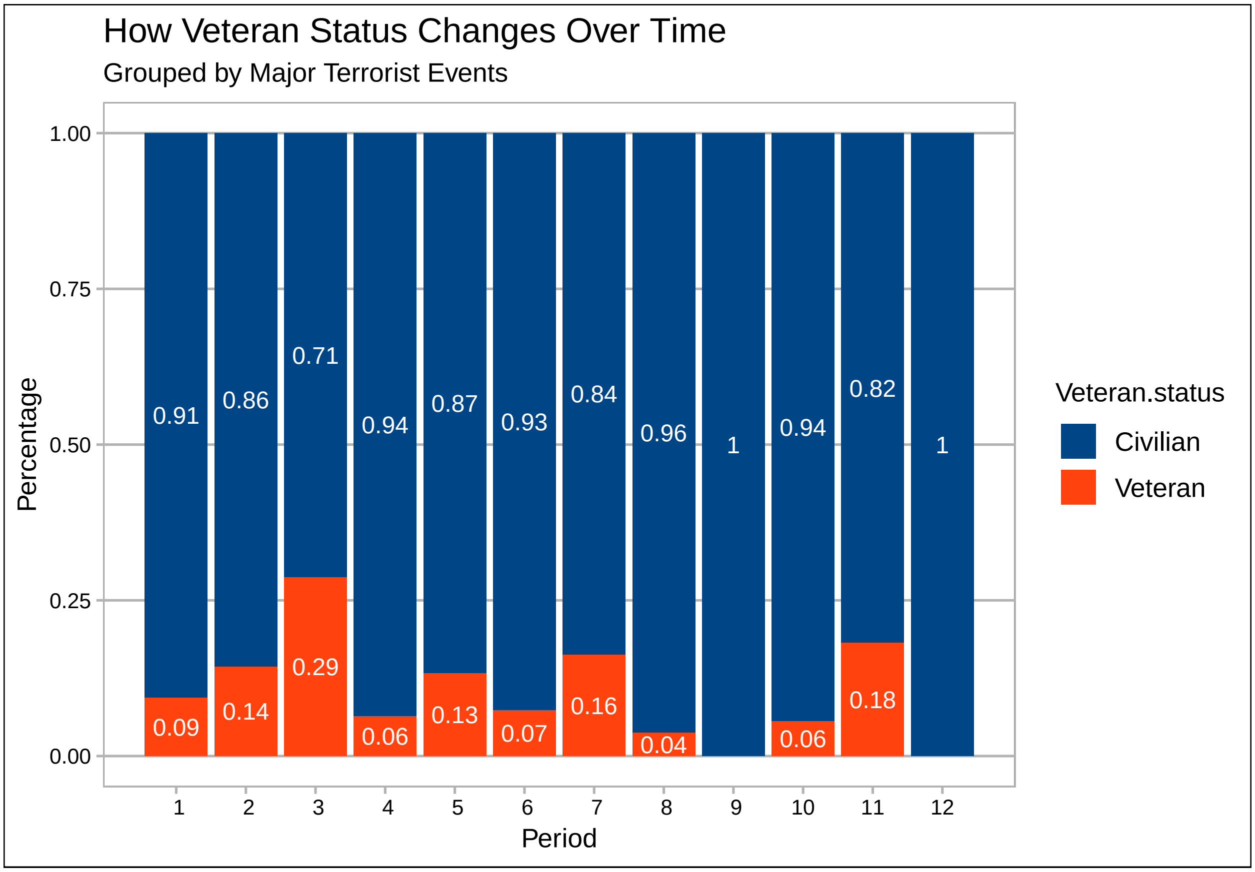

```
# Religion: Unkown, Muslin, Christian
# Delete these categories
test3 <- prosNEW[which(Religion != "Other" & Religion != "Jewish"),]
# Change Chritian Identity to Christian
test3 <- test3 %>%
  mutate(Religion = ifelse(Religion == "Unknown", "Unknown",
                           ifelse(Religion == "Christian", "Christian",
                                  ifelse(Religion == "Christian Identity", "Christian",
                                         "Muslim"))))
religion.count <- test3 %>%
  dplyr::group_by(Religion, Period) %>%
  dplyr::summarise(n = n()) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::group_by(Period) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::mutate(freq = round(freq,digits=2))
```

```r
ggplot(religion.count, aes(x=Period, y=n, fill=Religion)) +
  geom_bar(size=2, stat="identity", position="fill") +
  scale_x_discrete(name ="Period", limits=c(1:12)) +
  theme_minimal() +
  labs(y="Percentage", title="How Religion Changes Over Time",
       subtitle="Grouped by Major Terrorist Events") +
  geom_text(aes(label=freq),stat='identity',
            position=position_fill(vjust=0.5),color="white",size=3) +
  theme_calc() + scale_fill_calc()
```



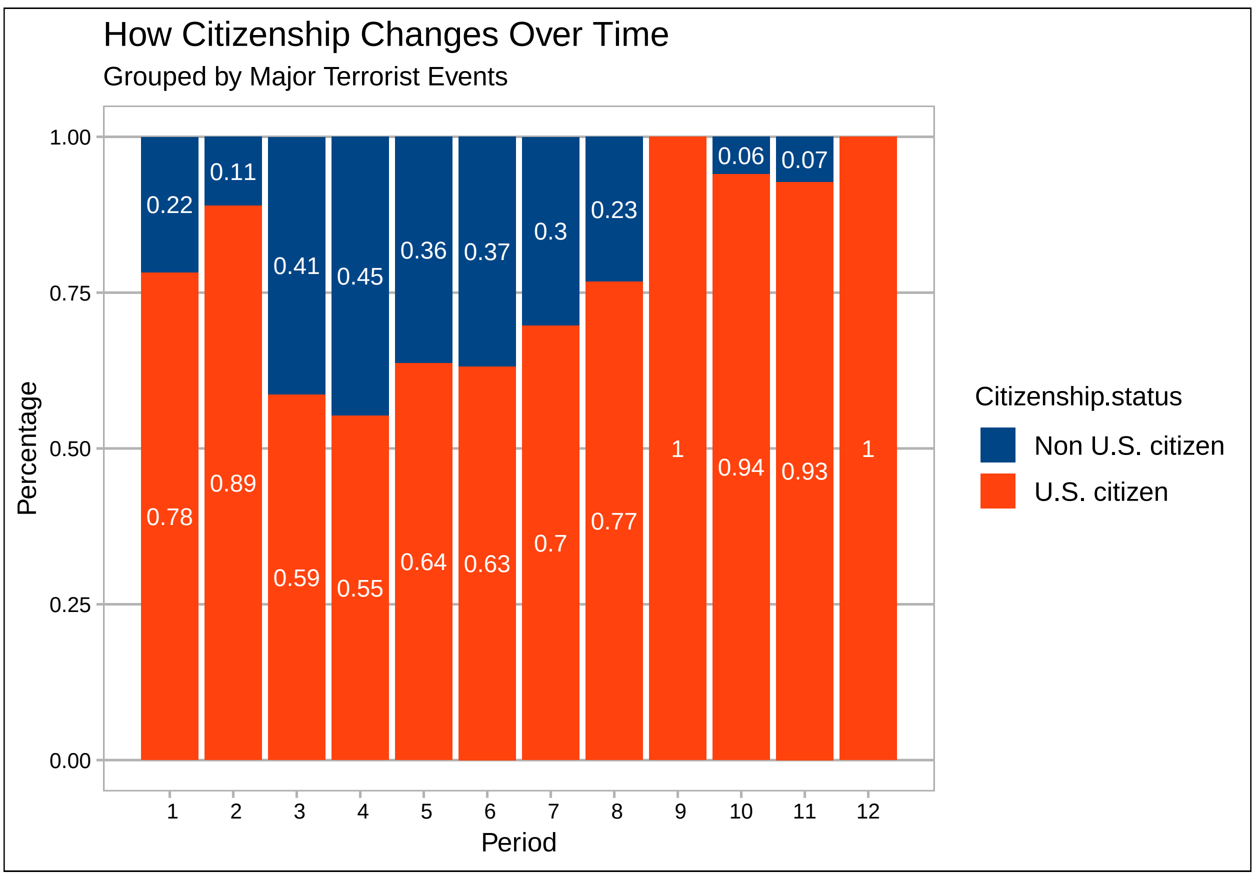

```r
# Veteran: Civilian and Veteran
# Delete unknowns
test4 <- prosNEW[which(Veteran.status != "Unknown"),]
# Only keep civilian and veteran categories
test4 <- test4 %>%
  mutate(Veteran.status = ifelse(Veteran.status == "Civilian", "Civilian",
                                 "Veteran"))

veteran.count <- test4 %>%
  dplyr::group_by(Veteran.status, Period) %>%
  dplyr::summarise(n = n()) %>%
```

```r
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::group_by(Period) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::mutate(freq = round(freq,digits=2))

ggplot(veteran.count, aes(x=Period, y=n, fill=Veteran.status)) +
  geom_bar(size=2, stat="identity", position="fill") +
  scale_x_discrete(name ="Period", limits=c(1:12)) +
  theme_minimal() +
  labs(y="Percentage", title="How Veteran Status Changes Over Time",
       subtitle="Grouped by Major Terrorist Events") +
  geom_text(aes(label=freq),stat='identity',
            position=position_fill(vjust=0.5),color="white",size=3) +
  theme_calc() + scale_fill_calc()
```

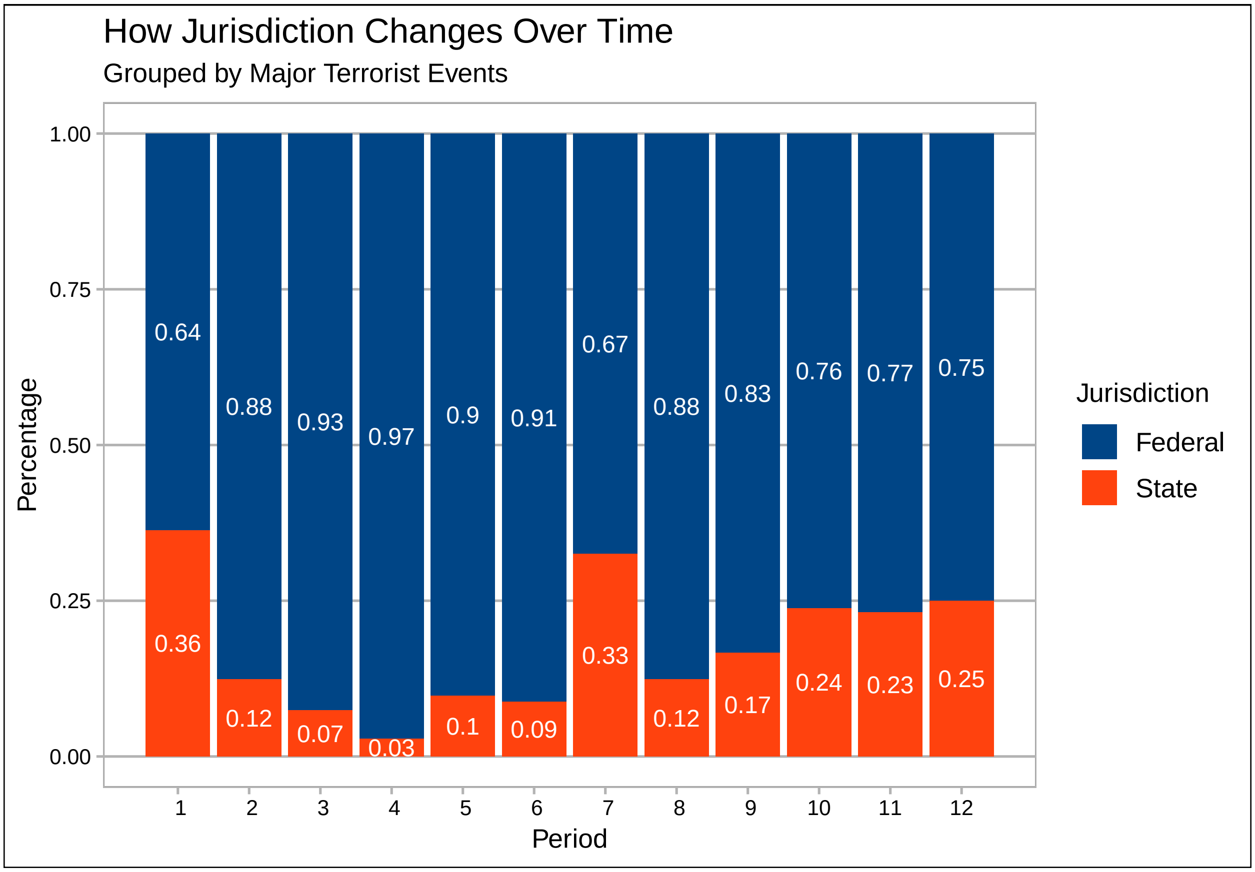



```r
# Citizenship Status: US and Non-US Citizen
# Delete unknowns
test5 <- prosNEW[which(Citizenship.status != "Unknown"),]
# Change to only include US and non US citizens
test5 <- test5 %>%
  mutate(Citizenship.status = ifelse(Citizenship.status == "U.S. citizen", "U.S. citizen
```

```
                                                    "Non U.S. citizen"))

citizen.count <- test5 %>%
  dplyr::group_by(Citizenship.status, Period) %>%
  dplyr::summarise(n = n()) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::group_by(Period) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::mutate(freq = round(freq,digits=2))

ggplot(citizen.count, aes(x=Period, y=n, fill=Citizenship.status)) +
  geom_bar(size=2, stat="identity", position="fill") +
  scale_x_discrete(name ="Period", limits=c(1:12)) +
  theme_minimal() +
  labs(y="Percentage", title="How Citizenship Changes Over Time",
       subtitle="Grouped by Major Terrorist Events") +
  geom_text(aes(label=freq),stat='identity',
            position=position_fill(vjust=0.5),color="white",size=3) +
  theme_calc() + scale_fill_calc()
```

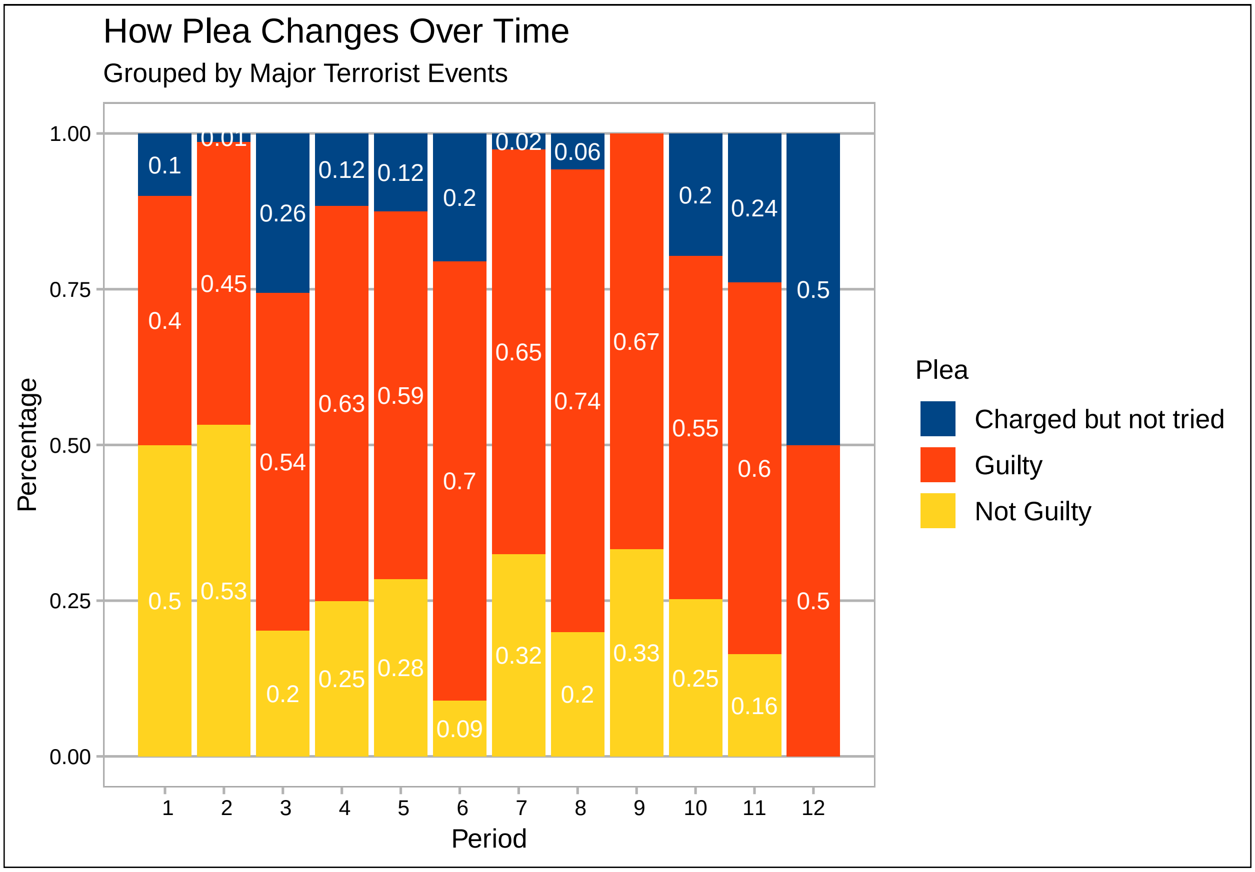


```r
# Jurisdiction: Federal and State
# Delete # (unknowns)
test6 <- prosNEW[which(Jurisdiction != "#"),]
# Remove spaces to clean category names
test6$Jurisdiction <- gsub(" ", "", test6$Jurisdiction, fixed = TRUE)

jurisdiction.count <- test6 %>%
  dplyr::group_by(Jurisdiction, Period) %>%
  dplyr::summarise(n = n()) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::group_by(Period) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::mutate(freq = round(freq,digits=2))

ggplot(jurisdiction.count, aes(x=Period, y=n, fill=Jurisdiction)) +
  geom_bar(size=2, stat="identity", position="fill") +
  scale_x_discrete(name ="Period", limits=c(1:12)) +
  theme_minimal() +
  labs(y="Percentage", title="How Jurisdiction Changes Over Time",
       subtitle="Grouped by Major Terrorist Events") +
  geom_text(aes(label=freq),stat='identity',
            position=position_fill(vjust=0.5),color="white",size=3) +
  theme_calc() + scale_fill_calc()
```



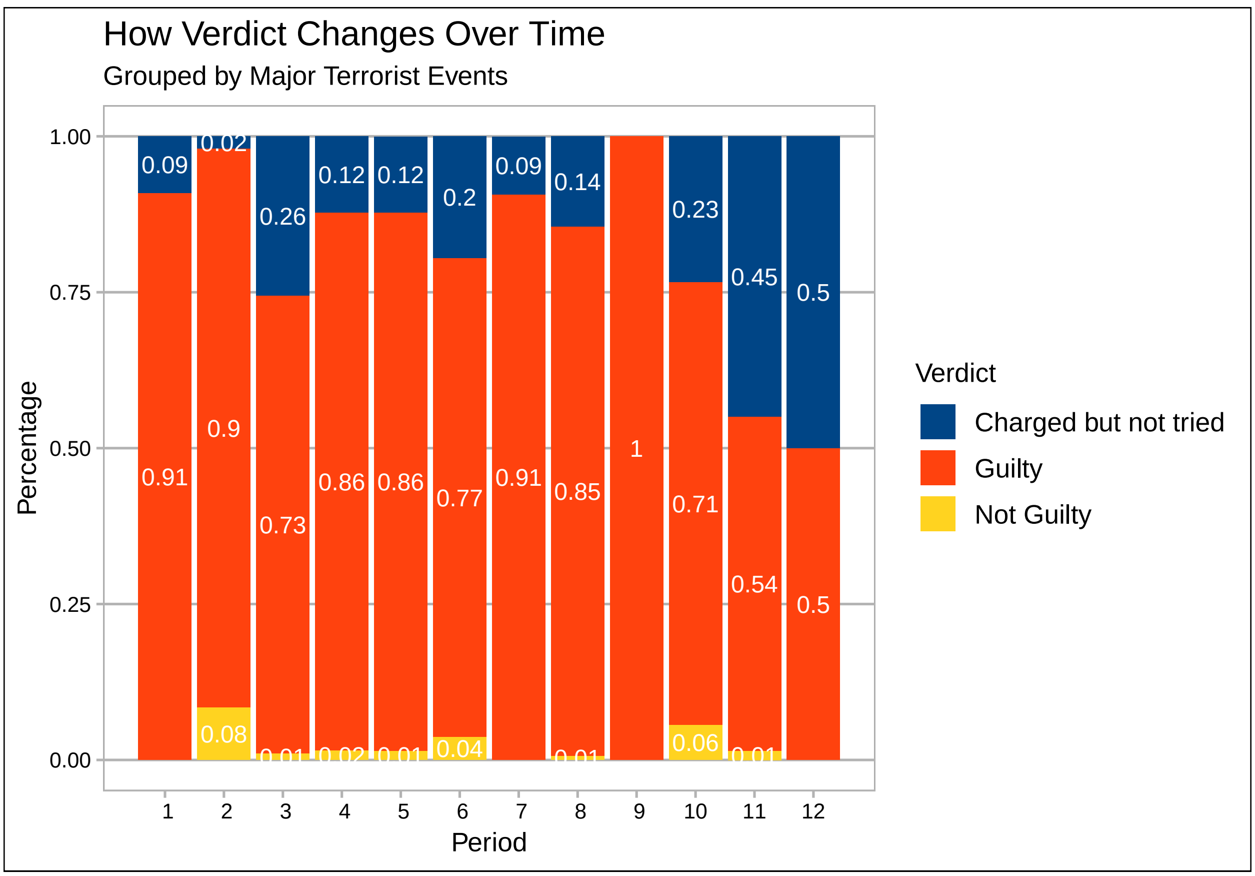

```r
# Plea: Guilty, Not Guilty, Charged & Pending
# Delete unkowns and no contest
test7 <- prosNEW[which(Plea != "Unknown" & Plea != "DATA NOT FOUND" &
                          Plea != "No contest"),]
# Change categories to only include guilty, not guilty, & charged not tried
test7 <- test7 %>%
  mutate(Plea = ifelse(Plea == "Guilty: plea bargain/blind plea", "Guilty",
                       ifelse(Plea == "Not guilty: blind plea", "Not Guilty",
                              ifelse(Plea == "Not guilty: special defense", "Not Guilty"
                                     "Charged but not tried"))))

plea.count <- test7 %>%
  dplyr::group_by(Plea, Period) %>%
  dplyr::summarise(n = n()) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::group_by(Period) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::mutate(freq = round(freq,digits=2))

ggplot(plea.count, aes(x=Period, y=n, fill=Plea)) +
  geom_bar(size=2, stat="identity", position="fill") +
```

```r
  scale_x_discrete(name ="Period", limits=c(1:12)) +
  theme_minimal() +
  labs(y="Percentage", title="How Plea Changes Over Time",
       subtitle="Grouped by Major Terrorist Events") +
  geom_text(aes(label=freq),stat='identity',
            position=position_fill(vjust=0.5),color="white",size=3) +
  theme_calc() + scale_fill_calc()
```



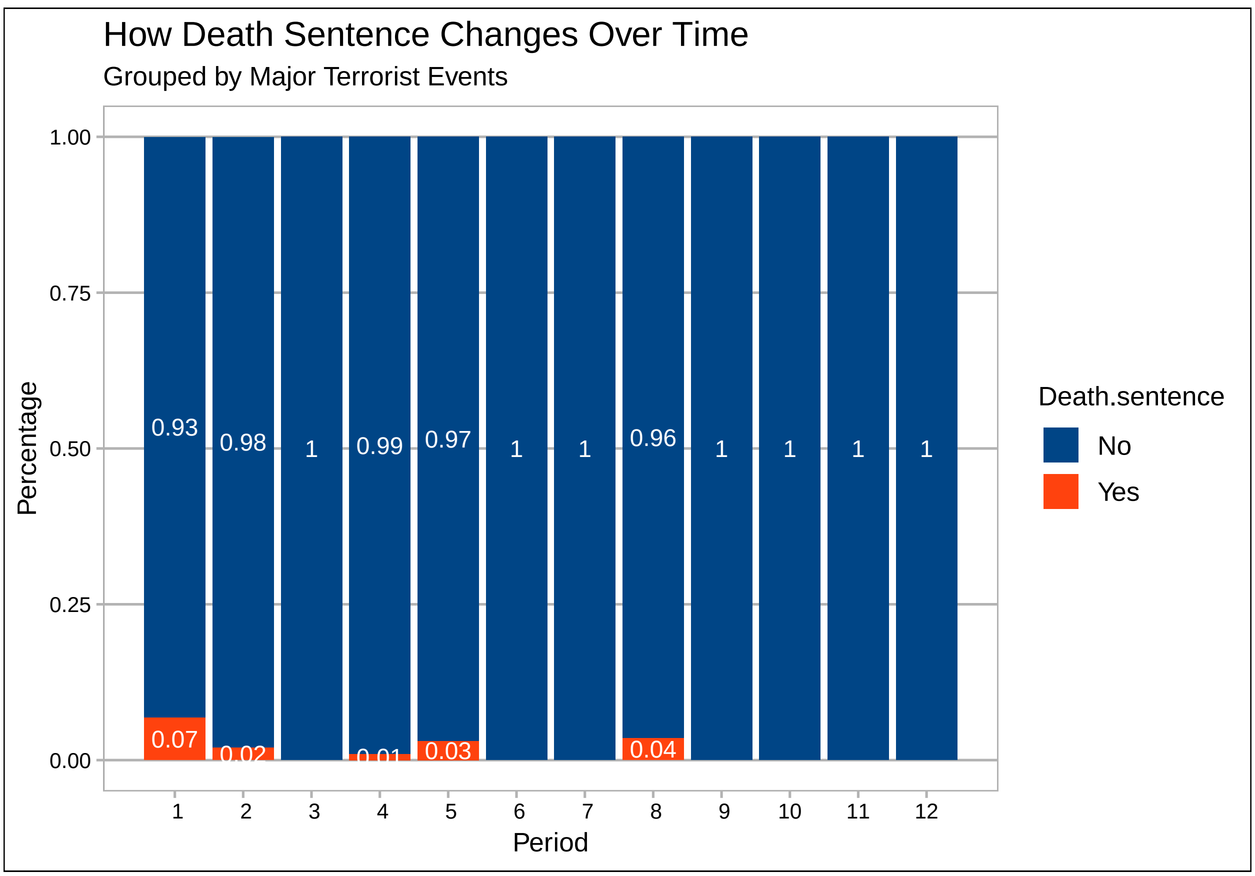

```r
# Verdict: Guilty, Not Guilty, Charged & Pending
# Delete the following categories
test8 <- prosNEW[which(Verdict != "Unknown" & Verdict != "Hung jury/mistrial"),]
# Remove unwanted spaces in category names
test8$Verdict <- gsub(" ", "", test8$Verdict, fixed = TRUE)
# Change categories to only include guilty, not guilty, & charged not tried
test8 <- test8 %>%
  mutate(Verdict = ifelse(Verdict == "Guilty", "Guilty",
                          ifelse(Verdict == "Guiltyonsomecharges/notguiltyonothers", "Gu
                                 ifelse(Verdict == "Notguilty", "Not Guilty",
                                 "Charged but not tried"))))

verdict.count <- test8 %>%
```

```r
  dplyr::group_by(Verdict, Period) %>%
  dplyr::summarise(n = n()) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::group_by(Period) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::mutate(freq = round(freq,digits=2))

ggplot(verdict.count, aes(x=Period, y=n, fill=Verdict)) +
  geom_bar(size=2, stat="identity", position="fill") +
  scale_x_discrete(name ="Period", limits=c(1:12)) +
  theme_minimal() +
  labs(y="Percentage", title="How Verdict Changes Over Time",
       subtitle="Grouped by Major Terrorist Events") +
  geom_text(aes(label=freq),stat='identity',
            position=position_fill(vjust=0.5),color="white",size=3) +
  theme_calc() + scale_fill_calc()
```

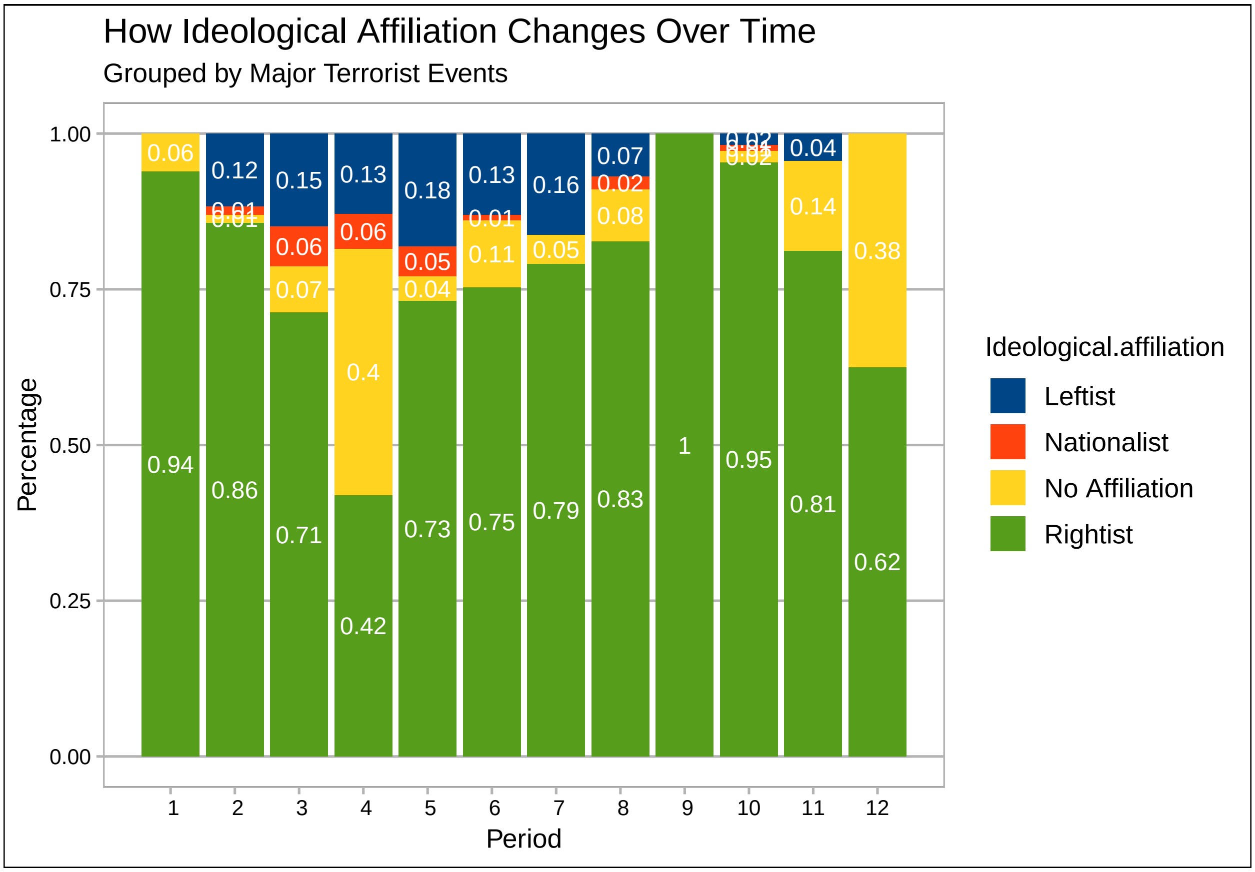



```r
# Death.Sentence: 0, 1
# Delete Unknowns
test9 <- prosNEW[which(Death.sentence != "#" & Death.sentence != "DATA NOT FOUND"),]
test9 <- test9 %>%
```

```
  mutate(Death.sentence = ifelse(Death.sentence == "1", "Yes",
                               "No"))

death.count <- test9 %>%
  dplyr::group_by(Death.sentence, Period) %>%
  dplyr::summarise(n = n()) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::group_by(Period) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::mutate(freq = round(freq,digits=2))

ggplot(death.count, aes(x=Period, y=n, fill=Death.sentence)) +
  geom_bar(size=2, stat="identity", position="fill") +
  scale_x_discrete(name ="Period", limits=c(1:12)) +
  theme_minimal() +
  labs(y="Percentage", title="How Death Sentence Changes Over Time",
       subtitle="Grouped by Major Terrorist Events") +
  geom_text(aes(label=freq),stat='identity',
            position=position_fill(vjust=0.5),color="white",size=3) +
  theme_calc() + scale_fill_calc()
```

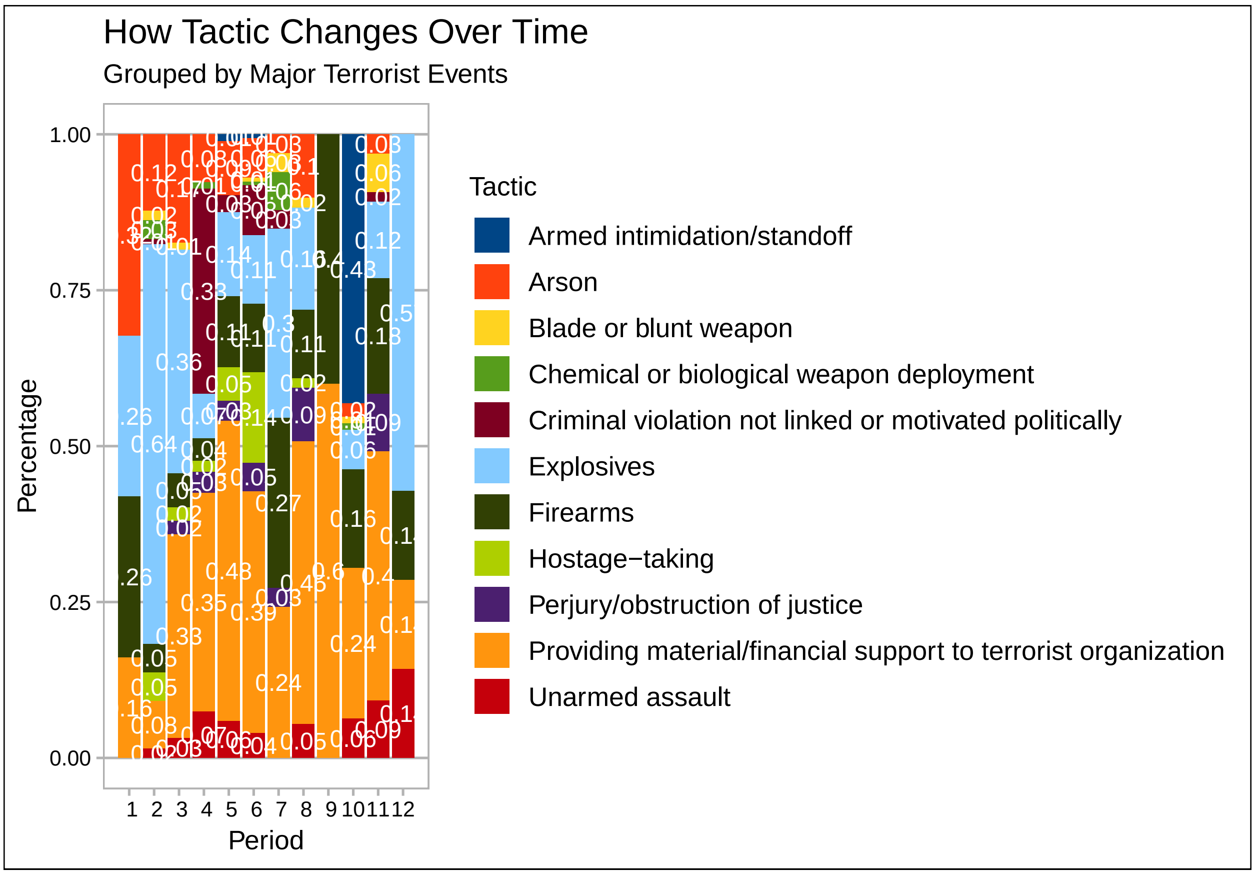


```r
# Ideological Affiliation: Leftist, Rightist, No Affiliation
# Change to only include leftist, nationalist, no affiliation, & rightist catg
test10 <- prosNEW %>%
  mutate(Ideological.affiliation = ifelse(Ideological.affiliation == "Leftist: eco-anima
                                   ifelse(Ideological.affiliation == "Leftist: governmen
                                   ifelse(Ideological.affiliation == "Leftist: identity-
                                   ifelse(Ideological.affiliation == "Nationalist-separa
                                   ifelse(Ideological.affiliation == "Unclear", "No Affi
                                   ifelse(Ideological.affiliation == "No affiliation/not
                                   ifelse(Ideological.affiliation == "Other", "No Affili

ideol.count <- test10 %>%
  dplyr::group_by(Ideological.affiliation, Period) %>%
  dplyr::summarise(n = n()) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::group_by(Period) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::mutate(freq = round(freq,digits=2))

ggplot(ideol.count, aes(x=Period, y=n, fill=Ideological.affiliation)) +
  geom_bar(size=2, stat="identity", position="fill") +
  scale_x_discrete(name ="Period", limits=c(1:12)) +
  theme_minimal() +
  labs(y="Percentage", title="How Ideological Affiliation Changes Over Time",
       subtitle="Grouped by Major Terrorist Events") +
  geom_text(aes(label=freq),stat='identity',
            position=position_fill(vjust=0.5),color="white",size=3) +
  theme_calc() + scale_fill_calc()
```



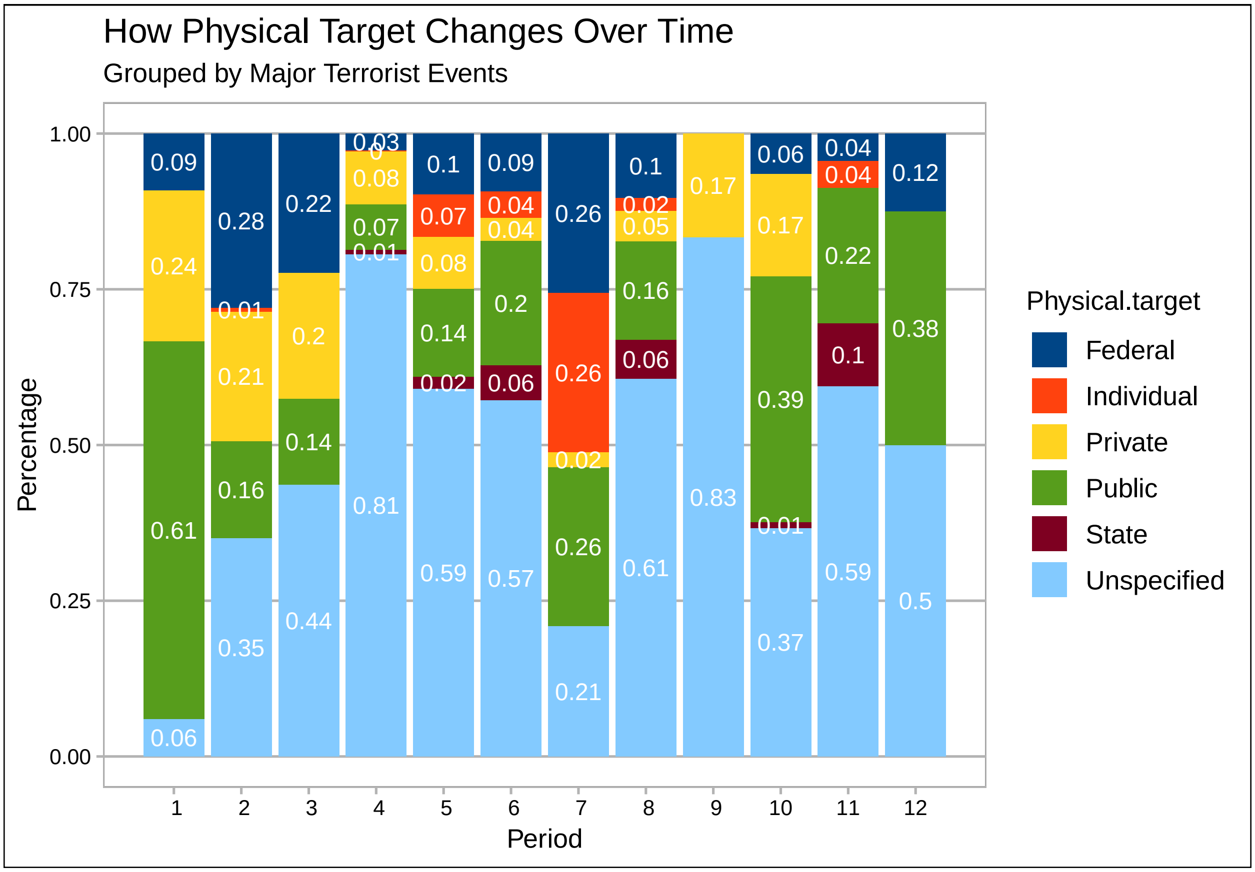

```r
# Tactic: Unarmed Assault: Vandalism & Below, and keep rest
# Delete following categories
test11 <- prosNEW[which(Tactic != "Other" & Tactic != "Various methods"),]
# Change categories to only include top tactics
test11 <- test11 %>%
  mutate(Tactic = ifelse(Tactic == "Providing material/financial support to terrorist or
                  ifelse(Tactic == "Explosives", "Explosives",
                  ifelse(Tactic == "Various methods", "Various methods",
                  ifelse(Tactic == "Criminal violation not linked or motivated politica
                  ifelse(Tactic == "Arson", "Arson",
                  ifelse(Tactic == "Firearms: civilian", "Firearms",
                  ifelse(Tactic == "Firearms: military", "Firearms",
                  ifelse(Tactic == "Hostage-taking", "Hostage-taking",
                  ifelse(Tactic == "Perjury/obstruction of justice", "Perjury/obstructi
                  ifelse(Tactic == "Armed intimidation/standoff", "Armed intimidation/s
                  ifelse(Tactic == "Blade or blunt weapon", "Blade or blunt weapon",
                  ifelse(Tactic == "Chemical or biological weapon deployment", "Chemica
                                   "Unarmed assault"))))))))))))

tactic.count <- test11 %>%
  dplyr::group_by(Tactic, Period) %>%
```

```r
  dplyr::summarise(n = n()) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::group_by(Period) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::mutate(freq = round(freq,digits=2))

ggplot(tactic.count, aes(x=Period, y=n, fill=Tactic)) +
  geom_bar(size=2, stat="identity", position="fill") +
  scale_x_discrete(name ="Period", limits=c(1:12)) +
  theme_minimal() +
  labs(y="Percentage", title="How Tactic Changes Over Time",
       subtitle="Grouped by Major Terrorist Events") +
  geom_text(aes(label=freq),stat='identity',
            position=position_fill(vjust=0.5),color="white",size=3) +
  theme_calc() + scale_fill_calc()
```



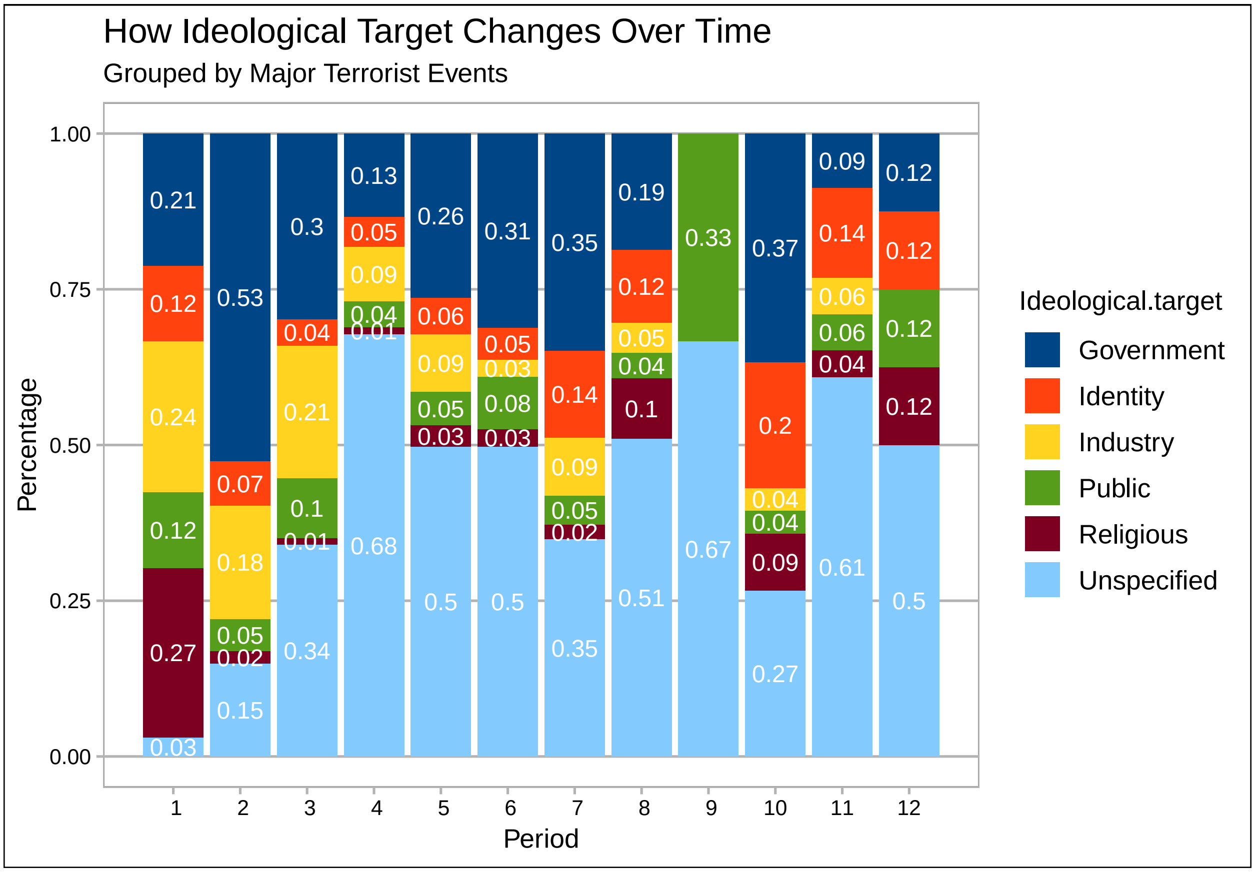

```r
# Physical.Target: Federal, State, Public, Mass Transport
# Only include above listed categories
test12 <- prosNEW %>%
  mutate(Physical.target = ifelse(Physical.target == "Unspecified/unknown/undeveloped",
                                  ifelse(Physical.target == "No direct target", "Unspecified",
```

```
                              ifelse(Physical.target == "Private site: business/corporate p
                              ifelse(Physical.target == "Multiple types", "Unspecified",
                              ifelse(Physical.target == "Federal site: military", "Federal"
                              ifelse(Physical.target == "Federal site: non-military non-jud
                              ifelse(Physical.target == "Private site: residential", "Priva
                              ifelse(Physical.target == "Individual person(s)", "Individual
                              ifelse(Physical.target == "Municipal: local law enforcement",
                              ifelse(Physical.target == "Federal site: non-U.S. embassy or
                              ifelse(Physical.target == "Federal site: judicial", "Federal"
                              ifelse(Physical.target == "Online", "Unspecified",
                              ifelse(Physical.target == "State site: non-military non-judic
                              ifelse(Physical.target == "State site: judicial", "State", "P

physical.count <- test12 %>%
  dplyr::group_by(Physical.target, Period) %>%
  dplyr::summarise(n = n()) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::group_by(Period) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::mutate(freq = round(freq,digits=2))

ggplot(physical.count, aes(x=Period, y=n, fill=Physical.target)) +
  geom_bar(size=2, stat="identity", position="fill") +
  scale_x_discrete(name ="Period", limits=c(1:12)) +
  theme_minimal() +
  labs(y="Percentage", title="How Physical Target Changes Over Time",
       subtitle="Grouped by Major Terrorist Events") +
  geom_text(aes(label=freq),stat='identity',
            position=position_fill(vjust=0.5),color="white",size=3) +
  theme_calc() + scale_fill_calc()
```

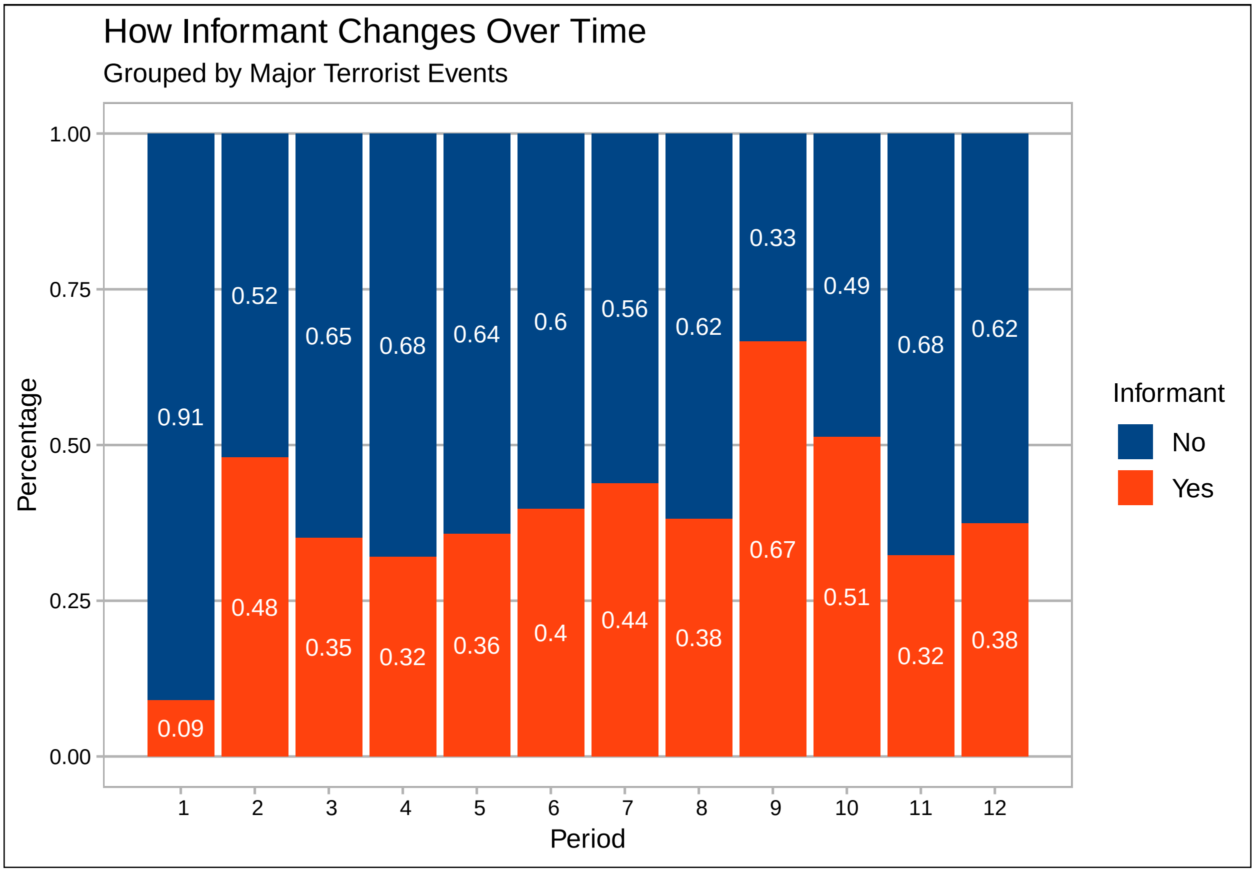



```r
# Ideological.Target: Unspecified, Government, Identity,
#                     Religious, Industry
# Change to only include above listed categories
test13 <- prosNEW %>%
  mutate(Ideological.target = ifelse(Ideological.target == "Unspecified", "Unspecified",
                                     ifelse(Ideological.target == "Multiple motivations"
                                     ifelse(Ideological.target == "Identity: race/ethnic
                                     ifelse(Ideological.target == "General public", "Pub
                                     ifelse(Ideological.target == "Industry: animal prod
                                     ifelse(Ideological.target == "Industry: abortion",
                                     ifelse(Ideological.target == "Religious: Muslim", "
                                     ifelse(Ideological.target == "Industry: private cor
                                     ifelse(Ideological.target == "Industry: land develo
                                     ifelse(Ideological.target == "Identity: nationality
                                     ifelse(Ideological.target == "Religious: Jewish", "
                                     ifelse(Ideological.target == "Religious: other", "R
                                     ifelse(Ideological.target == "Identity: political a
                                     ifelse(Ideological.target == "Industry: technology/
                                     ifelse(Ideological.target == "Identity: sexuality",
                                     ifelse(Ideological.target == "Industry: place of at
                                     ifelse(Ideological.target == "Religious: Christian"
```

```r
                                    ifelse(Ideological.target == "Industry: adult enter
                                    ifelse(Ideological.target == "Religious: Jewish", "
                                           "Government"))))))))))))))))))))
test13$Ideological.target <- gsub(" ", "", test13$Ideological.target, fixed = TRUE)

target.count <- test13 %>%
  dplyr::group_by(Ideological.target, Period) %>%
  dplyr::summarise(n = n()) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::group_by(Period) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::mutate(freq = round(freq,digits=2))

ggplot(target.count, aes(x=Period, y=n, fill=Ideological.target)) +
  geom_bar(size=2, stat="identity", position="fill") +
  scale_x_discrete(name ="Period", limits=c(1:12)) +
  theme_minimal() +
  labs(y="Percentage", title="How Ideological Target Changes Over Time",
       subtitle="Grouped by Major Terrorist Events") +
  geom_text(aes(label=freq),stat='identity',
            position=position_fill(vjust=0.5),color="white",size=3) +
  theme_calc() + scale_fill_calc()
```

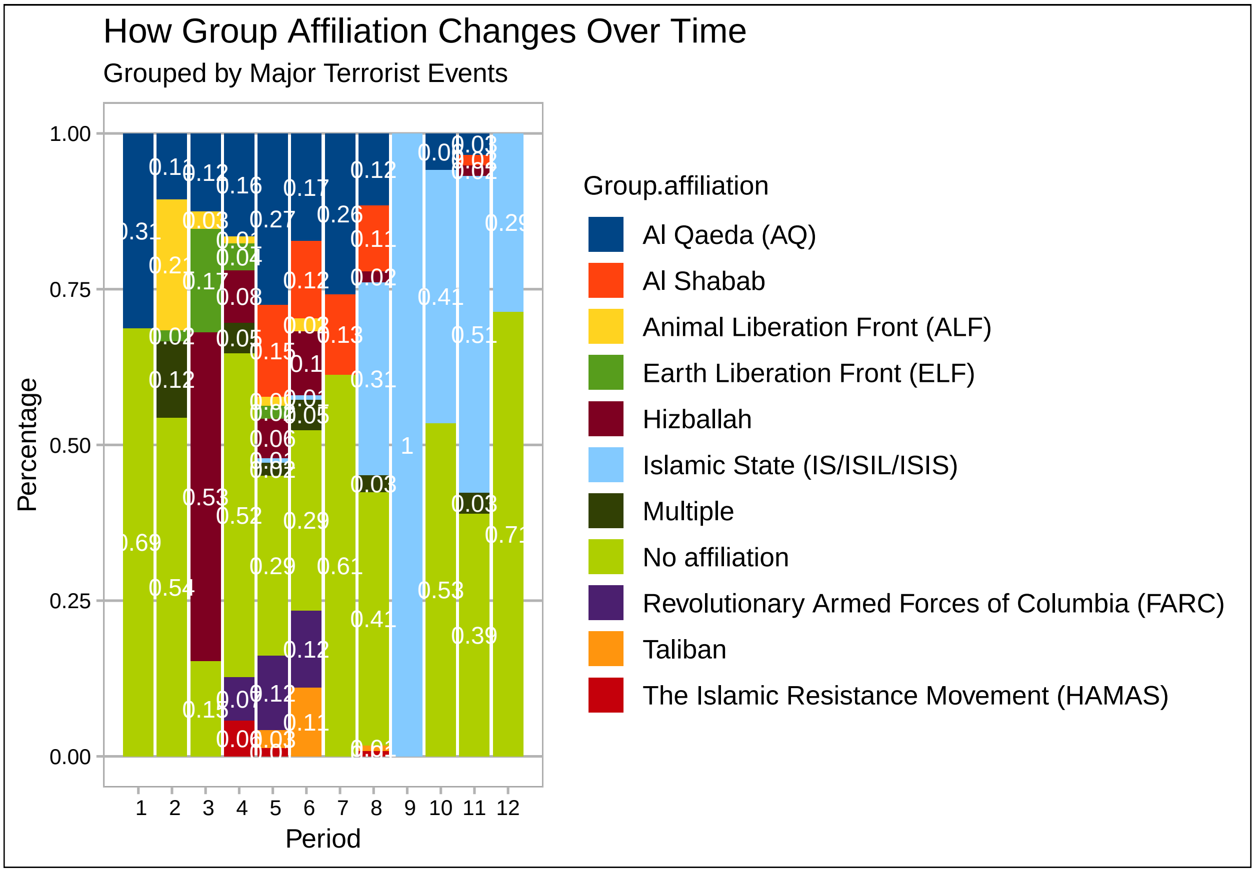



```
# Informant: Yes and No
# Delete unknowns
test14 <- prosNEW[which(Informant != "Presumed but not documented" & Informant != "Unkno

informant.count <- test14 %>%
  dplyr::group_by(Informant, Period) %>%
  dplyr::summarise(n = n()) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::group_by(Period) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::mutate(freq = round(freq,digits=2))

ggplot(informant.count, aes(x=Period, y=n, fill=Informant)) +
  geom_bar(size=2, stat="identity", position="fill") +
  scale_x_discrete(name ="Period", limits=c(1:12)) +
  theme_minimal() +
  labs(y="Percentage", title="How Informant Changes Over Time",
       subtitle="Grouped by Major Terrorist Events") +
  geom_text(aes(label=freq),stat='identity',
            position=position_fill(vjust=0.5),color="white",size=3) +
  theme_calc() + scale_fill_calc()
```



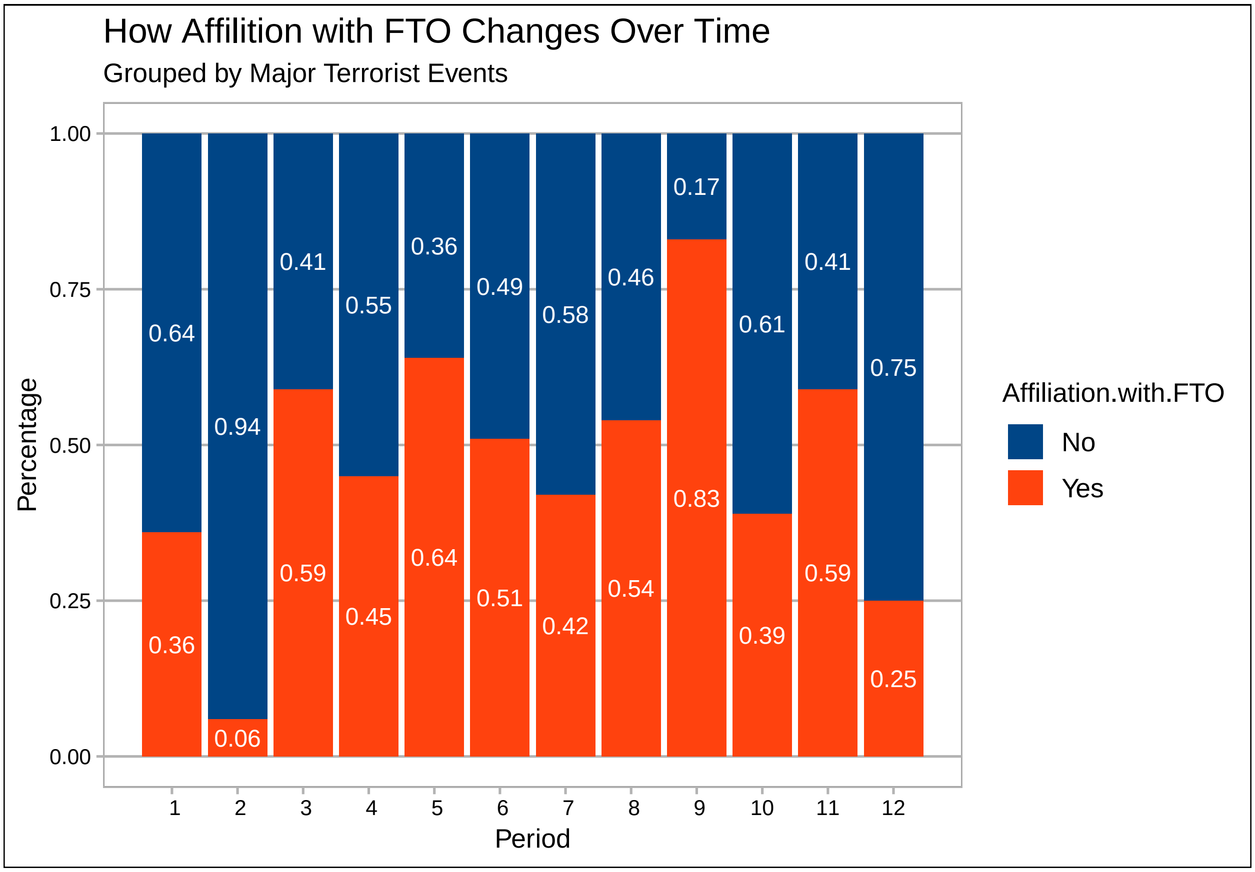

```
# Group.Affiliation: Only >20 Keep
# Change to only include top group categories
test15 <- prosNEW[which(Group.affiliation == "No affiliation" | Group.affiliation == "Al
                          Group.affiliation == "Islamic State (IS/ISIL/ISIS)" | Group.af
                          Group.affiliation == "Revolutionary Armed Forces of Columbia (
                          Group.affiliation == "Al Shabab" | Group.affiliation == "Multi
                          Group.affiliation == "Earth Liberation Front (ELF)" | Group.af
                          Group.affiliation == "The Islamic Resistance Movement (HAMAS)"

group.count <- test15 %>%
  dplyr::group_by(Group.affiliation, Period) %>%
  dplyr::summarise(n = n()) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::group_by(Period) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::mutate(freq = round(freq,digits=2))


ggplot(group.count, aes(x=Period, y=n, fill=Group.affiliation)) +
  geom_bar(size=2, stat="identity", position="fill") +
  scale_x_discrete(name ="Period", limits=c(1:12)) +
```

```r
  theme_minimal() +
  labs(y="Percentage", title="How Group Affiliation Changes Over Time",
       subtitle="Grouped by Major Terrorist Events") +
  geom_text(aes(label=freq),stat='identity',
            position=position_fill(vjust=0.5),color="white",size=3) +
  theme_calc() + scale_fill_calc()
```




```r
# Affiliation.with.FTO: Yes and No
# Delete unknowns
test16 <- prosNEW[which(Affiliation.with.FTO != "Unknown"),]
test16$Affiliation.with.FTO <- gsub(" ", "", test16$Affiliation.with.FTO, fixed = TRUE)

aff.count <- test16 %>%
  dplyr::group_by(Affiliation.with.FTO, Period) %>%
  dplyr::summarise(n = n()) %>%
  dplyr::group_by(Period) %>%
  dplyr::mutate(freq = n / sum(n)) %>%
  dplyr::mutate(freq = round(freq,digits=2))


ggplot(aff.count, aes(x=Period, y=freq, fill=Affiliation.with.FTO)) +
```

```
  geom_bar(size=2, stat="identity", position="fill") +
  scale_x_discrete(name ="Period", limits=c(1:12)) +
  theme_minimal() +
  labs(y="Percentage", title="How Affilition with FTO Changes Over Time",
       subtitle="Grouped by Major Terrorist Events") +
  geom_text(aes(label=freq),stat='identity',
            position=position_fill(vjust=0.5),color="white",size=3) +
  theme_calc() + scale_fill_calc()
```



0.4.3 Contingency Tables, Stacked Bar Plot, & Statistical Analysis Code

```
##########################################################################################
# tPP Contingency Table Analysis Code
# Author: Daniel Cirkovic (cirkovd@miamioh.edu)
# Purpose: 1. Organize Variables into Contignecy Tables comparing period and different
#          2. Analyze the Contignecy Tables using Chi-Square Tests and Fisher Exact Te
#          3. Perform Cochran Mantel Haenszel Tests on "3D" Contingency tables
#          4. Create graphics for the "3D" table
```

```
#################################################################################################

# Set your working directory
# setwd("C:\\Users\\Daniel\\Desktop\\STA475\\tPP")

# Libraries (use install.packages() if not already installed)
library(lubridate) # used to tackle date strings
library(tidyverse) # ggplot, dplyr, etc
```

```
## Warning: package 'tidyverse' was built under R version 3.5.2

## -- Attaching packages ---------------------------------- tidyverse 1.2.1 --

## v tibble  1.4.2     v purrr   0.2.5
## v tidyr   0.8.1     v stringr 1.3.1
## v readr   1.1.1     v forcats 0.3.0

## -- Conflicts ------------------------------------- tidyverse_conflicts() --
## x lubridate::as.difftime() masks base::as.difftime()
## x lubridate::date()        masks base::date()
## x dplyr::filter()          masks stats::filter()
## x lubridate::intersect()   masks base::intersect()
## x dplyr::lag()             masks stats::lag()
## x lubridate::setdiff()     masks base::setdiff()
## x lubridate::union()       masks base::union()
```

```
library(psych)     # used to CMH tests (3D table)
```

```
## Warning: package 'psych' was built under R version 3.5.3

##
## Attaching package: 'psych'

## The following objects are masked from 'package:ggplot2':
##
##     %+%, alpha
```

```
# General Data Cleaning
  # Here is where we group into periods. Periods can be easily adjusted by changing th

pros <- read.csv(file="U__FOUO Spreadsheet - CLEAN.csv")
pros <- pros %>%
  mutate(Date = mdy(Date))

### Create new 'Period' variabe that separates events into one of the 9 periods where te
# (1) Oklahoma City (Apr 19, 1995) (Before)
# (2) Oklahoma City (Apr 19, 1995) (After)
# (3) Columbine (Apr 20, 1999) (After)
```

```r
# (4) 9/11 (Sept 11, 2001) (After)
# (5) Capitol Hill Massacre (03/25/2006) (After)
# (6) Fort Hood (Feb 26, 2009) (After)
# (7) Trayvon Martin (Feb 26, 2012) (After)
# (8) Sandy Hook (Dec 14, 2012) (After)
# (9) Charleston (June 17, 2015) (After)
# (10) Aurora (July 20, 2015) (After)
# (11) Orlando Night Club (June 12, 2016) (After)
# (12) Parkland School (Feb 14, 2018) (After)


prosNEW <- pros %>%
  mutate(Period = ifelse(Date <= '1995-04-19', 1,
                       ifelse(Date > '1995-04-19' & Date <= '1999-04-20', 2,
                              ifelse(Date > '1999-04-20' & Date <= '2001-09-11', 3,
                                     ifelse(Date > '2001-09-11' & Date <= '2006-03-25'
                                            ifelse(Date > '2006-03-25' & Date <= '2009
                                                   ifelse(Date > '2009-11-05' & Date <
                                                          ifelse(Date > '2012-02-26' &
                                                                 ifelse(Date > '2012-1
                                                                        ifelse(Date >
                                                                               ifelse(




# Each variable is listed below. Under each variable, tables are aggregated, chi-squar
# Further, contingency tables are created with column proportions (for loops). They ar
# working directory. Then, if needed, copy and paste the notepad text into word and us

## age ##

Clean <- prosNEW %>%
  filter(Age != "#") %>%
  mutate(Age.group = cut(as.numeric(Age), c(0,20, seq(30,70, by=10)))) %>%
  arrange(as.numeric(Age))

tab <- table(Clean$Age.group, Clean$Period)

# Chi sq
chisq.test(tab)
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect

##
```

```
##  Pearson's Chi-squared test
##
## data:  tab
## X-squared = 90.329, df = 55, p-value = 0.001886
```

```r
chisq.test(tab)$expected  #<5's
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
##
##                    1          2          3           4         5
##   (0,20]  15.52589351 79.2355945 38.0116703 200.2304887 99.044493
##   (20,30]  6.26112327 31.9533187 15.3289570  80.7469001 39.941648
##   (30,40]  4.16703136 21.2662290 10.2020423  53.7403355 26.582786
##   (40,50]  2.30561634 11.7665937  5.6447848  29.7345004 14.708242
##   (50,60]  0.67687819  3.4544128  1.6571845   8.7293946  4.318016
##   (60,70]  0.06345733  0.3238512  0.1553611   0.8183807  0.404814
##
##                    6          7          8         9         10
##   (0,20]  105.4690007 23.0211524 73.8818381 3.2122538 55.1436907
##   (20,30]  42.5324581  9.2837345 29.7943107 1.2954048 22.2377826
##   (30,40]  28.3070751  6.1787017 19.8293217 0.8621444 14.8001459
##   (40,50]  15.6622903  3.4186725 10.9715536 0.4770241  8.1889132
##   (50,60]   4.5981036  1.0036470  3.2210066 0.1400438  2.4040846
##   (60,70]   0.4310722  0.0940919  0.3019694 0.0131291  0.2253829
##
##                  11         12
##   (0,20]  36.9409190 4.28300511
##   (20,30] 14.8971554 1.72720642
##   (30,40]  9.9146608 1.14952589
##   (40,50]  5.4857768 0.63603209
##   (50,60]  1.6105033 0.18672502
##   (60,70]  0.1509847 0.01750547
```

```r
# Fisher
fisher.test(tab, simulate.p.value = T, B=2000) #Monte carlo sims
```

```
##
##  Fisher's Exact Test for Count Data with simulated p-value (based
##  on 2000 replicates)
##
## data:  tab
## p-value = 0.0004998
## alternative hypothesis: two.sided
```

```r
# column proportions
for (j in 1:ncol(tab)){
```

```r
  c <- as.numeric(tab[,j])
  b <- sum(c)
  for (i in 1:nrow(tab)){
    a <- as.numeric(tab[i,j])
    prop <- a/b
    tab[i,j] <- paste(a, round(prop,2), sep="; ")
  }
}

tab <- summary(as.numeric(as.character(Clean$Age)), na.rm=T)
```

```
## Warning in summary(as.numeric(as.character(Clean$Age)), na.rm = T): NAs
## introduced by coercion
```

```r
#write.table(tab, file = "tab.txt", sep = ",", quote = FALSE, row.names = T)

## gender ##

levels(prosNEW$Gender)
```

```
## [1] "Female"                            "Male"
## [3] "Male "                             "Non-binary/gender non-conforming"
## [5] "Unknown/unclear"
```

```r
tab <- table(prosNEW$Gender, prosNEW$Period)
tab[2,] <- tab[2, ] + tab[3, ]
tab <- tab[c(1,2),]

# Chi sq
chisq.test(tab) ## FAIL TO REJECT
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect

##
##  Pearson's Chi-squared test
##
## data:  tab
## X-squared = 14.533, df = 11, p-value = 0.2049
```

```r
chisq.test(tab)$expected  #<5's
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect

##
##                  1         2         3        4         5         6
##   Female  2.589928  12.08633  7.377371  35.3172  16.08895  16.79529
##   Male   30.410072 141.91367 86.622629 414.6828 188.91105 197.20471
##
```

```
##                    7          8        9         10         11         12
##   Female  3.374755  11.37999 0.470896  8.476128  5.415304 0.6278613
##   Male   39.625245 133.62001 5.529104 99.523872 63.584696 7.3721387
```

```r
#Cramer's V
sqrt(chisq.test(tab)$statistic/(sum(tab) * (min(nrow(tab), ncol(tab)) - 1)))
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
##  X-squared
## 0.09749152
```

```r
# Fisher
fisher.test(tab, simulate.p.value = T, B=2000) #Monte carlo sims ########FAIL TO REJECT
```

```
##
##  Fisher's Exact Test for Count Data with simulated p-value (based
##  on 2000 replicates)
##
## data:  tab
## p-value = 0.3008
## alternative hypothesis: two.sided
```

```r
# column proportions
for (j in 1:ncol(tab)){
  c <- as.numeric(tab[,j])
  b <- sum(c)
  for (i in 1:nrow(tab)){
    a <- as.numeric(tab[i,j])
    prop <- a/b
    tab[i,j] <- paste(a, round(prop,2), sep="; ")
  }
}

write.table(tab, file = "tab2.txt", sep = ",", quote = FALSE, row.names = T)


## other status ##

levels(prosNEW$Other..status)
```

```
## [1] "Non-othered" "Othered"
```

```r
tab <- table(prosNEW$Other..status, prosNEW$Period)

# Chi sq
chisq.test(tab)
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
##
##  Pearson's Chi-squared test
##
## data:  tab
## X-squared = 240.82, df = 11, p-value < 2.2e-16
```

```r
chisq.test(tab)$expected  #<5's
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
##
##                     1        2        3        4         5        6
##   Non-othered 13.16982 61.45918 37.51404 179.5885  81.81254  85.8034
##   Othered     19.83018 92.54082 56.48596 270.4115 123.18746 129.1966
##
##                     7        8        9       10      11       12
##   Non-othered 17.16068 57.86741 2.394513 43.50033 27.5369 3.192685
##   Othered     25.83932 87.13259 3.605487 65.49967 41.4631 4.807315
```

```r
#Cramer's V
sqrt(chisq.test(tab)$statistic/(sum(tab) * (min(nrow(tab), ncol(tab)) - 1)))
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
## X-squared
## 0.3966089
```

```r
# Fisher
fisher.test(tab, simulate.p.value = T, B=2000) #Monte carlo sims
```

```
##
##  Fisher's Exact Test for Count Data with simulated p-value (based
##  on 2000 replicates)
##
## data:  tab
## p-value = 0.0004998
## alternative hypothesis: two.sided
```

```r
# column proportions
for (j in 1:ncol(tab)){
  c <- as.numeric(tab[,j])
  b <- sum(c)
  for (i in 1:nrow(tab)){
    a <- as.numeric(tab[i,j])
    prop <- a/b
    tab[i,j] <- paste(a, round(prop,2), sep="; ")
  }
```

```r
}

write.table(tab, file = "tab3.txt", sep = ",", quote = FALSE, row.names = T)


## ethnicity ##

levels(prosNEW$Racial.ethnic.group)
```

```
## [1] "American Indian/Alaska Native"  "Asian/South Asian"
## [3] "Biracial/Multiracial"           "Black/African/African American"
## [5] "Latino/Hispanic"                "Middle Eastern/North African"
## [7] "Unknown"                        "White/Caucasian"
```

```r
tab <- table(prosNEW$Racial.ethnic.group, prosNEW$Period)
tab <- tab[c(-7, -1, -3),]

# Chi sq
chisq.test(tab)
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
##
##  Pearson's Chi-squared test
##
## data:  tab
## X-squared = 338.62, df = 44, p-value < 2.2e-16
```

```r
chisq.test(tab)$expected  #<5's
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
##
##                                          1         2         3         4
##   Asian/South Asian               1.661871  7.256835  4.930216  20.77338
##   Black/African/African American  3.669065 16.021583 10.884892  45.86331
##   Latino/Hispanic                 1.812950  7.916547  5.378417  22.66187
##   Middle Eastern/North African    9.194245 40.148201 27.276259 114.92806
##   White/Caucasian                13.661871 59.656835 40.530216 170.77338
##
##                                         5        6         7         8
##   Asian/South Asian              11.02374 11.63309  2.326619  7.810791
##   Black/African/African American 24.33813 25.68345  5.136691 17.244604
##   Latino/Hispanic                12.02590 12.69065  2.538129  8.520863
##   Middle Eastern/North African   60.98849 64.35971 12.871942 43.212950
##   White/Caucasian                90.62374 95.63309 19.126619 64.210791
##
```

```
##                                              9         10         11         12
##   Asian/South Asian                 0.3323741  5.428777  3.434532 0.3877698
##   Black/African/African American 0.7338129 11.985612  7.582734 0.8561151
##   Latino/Hispanic                   0.3625899  5.922302  3.746763 0.4230216
##   Middle Eastern/North African   1.8388489 30.034532 19.001439 2.1453237
##   White/Caucasian                   2.7323741 44.628777 28.234532 3.1877698
```

```
#Cramer's V
sqrt(chisq.test(tab)$statistic/(sum(tab) * (min(nrow(tab), ncol(tab)) - 1)))
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
## X-squared
##  0.246786
```

```
# Fisher
fisher.test(tab, simulate.p.value = T, B=2000) #Monte carlo sims
```

```
##
##  Fisher's Exact Test for Count Data with simulated p-value (based
##  on 2000 replicates)
##
## data:  tab
## p-value = 0.0004998
## alternative hypothesis: two.sided
```

```
# column proportions
for (j in 1:ncol(tab)){
  c <- as.numeric(tab[,j])
  b <- sum(c)
  for (i in 1:nrow(tab)){
    a <- as.numeric(tab[i,j])
    prop <- a/b
    tab[i,j] <- paste(a, round(prop,2), sep="; ")
  }
}

write.table(tab, file = "tab4.txt", sep = ",", quote = FALSE, row.names = T)


## religion ##

levels(prosNEW$Religion)
```

```
## [1] "Christian"          "Christian Identity" "Jewish"
## [4] "Muslim"             "Muslim "            "Other"
## [7] "Unknown"
```

```r
tab <- table(prosNEW$Religion, prosNEW$Period)
tab[6,] <- tab[4,] + tab[5,]

tab <- tab[c(-3, -4,-5),]
rownames(tab) <- c("Christian", "Christian Identity", "Muslim", "Other")

# Chi sq
chisq.test(tab)
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect

##
##  Pearson's Chi-squared test
##
## data:  tab
## X-squared = 284.39, df = 33, p-value < 2.2e-16
```

```r
chisq.test(tab)$expected  #<5's
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect

##
##                              1          2          3          4          5
##   Christian           3.328467 15.129396  9.481088  45.18646 20.071666
##   Christian Identity  1.379562  6.270737  3.929662  18.72860  8.319177
##   Muslim             14.496350 65.892502 41.292634 196.79894 87.417386
##   Other              13.795620 62.707366 39.296616 187.28600 83.191772
##
##                              6          7          8          9         10
##   Christian          20.777704  4.337094 14.423358 0.6051758 10.89317
##   Christian Identity  8.611812  1.797611  5.978102 0.2508295  4.51493
##   Muslim             90.492369 18.889184 62.817518 2.6357001 47.44260
##   Other              86.118115 17.976111 59.781022 2.5082946 45.14930
##
##                             11         12
##   Christian           6.959522 0.8069011
##   Christian Identity  2.884539 0.3344393
##   Muslim             30.310551 3.5142668
##   Other              28.845388 3.3443928
```

```r
#Cramer's V
sqrt(chisq.test(tab)$statistic/(sum(tab) * (min(nrow(tab), ncol(tab)) - 1)))
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect

## X-squared
## 0.2508084
```

```r
# Fisher
fisher.test(tab, simulate.p.value = T, B=2000) #Monte carlo sims
```

```
##
##  Fisher's Exact Test for Count Data with simulated p-value (based
##  on 2000 replicates)
##
## data:  tab
## p-value = 0.0004998
## alternative hypothesis: two.sided
```

```r
# column proportions
for (j in 1:ncol(tab)){
  c <- as.numeric(tab[,j])
  b <- sum(c)
  for (i in 1:nrow(tab)){
    a <- as.numeric(tab[i,j])
    prop <- a/b
    tab[i,j] <- paste(a, round(prop,2), sep="; ")
  }
}

write.table(tab, file = "tab5.txt", sep = ",", quote = FALSE, row.names = T)


## veteran status ##

levels(prosNEW$Veteran.status)
```

```
## [1] "Active duty"
## [2] "Civilian"
## [3] "Civilian "
## [4] "Dishonorably discharged"
## [5] "Former/current member of non-U.S. military"
## [6] "Hardship discharge"
## [7] "Honorably discharged"
## [8] "Unknown"
```

```r
tab <- table(prosNEW$Veteran.status, prosNEW$Period)
tab[1,] <- tab[1,] + tab[4,] + tab[5,] + tab[6,] + tab[7,]
tab[2,] <- tab[2,] + tab[3,]
tab <- tab[c(1,2),]
rownames(tab) <- c("Veteran/Active Duty", "Civilian")

# Chi sq
chisq.test(tab)
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
##
##  Pearson's Chi-squared test
##
## data:  tab
## X-squared = 64.402, df = 11, p-value = 1.396e-09
```

```
chisq.test(tab)$expected  #<5's
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
##
##                              1          2          3          4          5
##   Veteran/Active Duty  3.234657  13.34296  9.501805  42.55596  17.48736
##   Civilian            28.765343 118.65704 84.498195 378.44404 155.51264
##
##                              6         7          8          9        10
##   Veteran/Active Duty  19.10469  4.34657  13.34296 0.6064982  8.99639
##   Civilian            169.89531 38.65343 118.65704 5.3935018 80.00361
##
##                             11        12
##   Veteran/Active Duty  6.67148 0.8086643
##   Civilian            59.32852 7.1913357
```

```
#Cramer's V
sqrt(chisq.test(tab)$statistic/(sum(tab) * (min(nrow(tab), ncol(tab)) - 1)))
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
## X-squared
##  0.215637
```

```
# Fisher
fisher.test(tab, simulate.p.value = T, B=2000) #Monte carlo sims
```

```
##
##  Fisher's Exact Test for Count Data with simulated p-value (based
##  on 2000 replicates)
##
## data:  tab
## p-value = 0.0004998
## alternative hypothesis: two.sided
```

```
# column proportions
for (j in 1:ncol(tab)){
  c <- as.numeric(tab[,j])
```

```r
  b <- sum(c)
  for (i in 1:nrow(tab)){
    a <- as.numeric(tab[i,j])
    prop <- a/b
    tab[i,j] <- paste(a, round(prop,2), sep="; ")
  }
}

write.table(tab, file = "tab6.txt", sep = ",", quote = FALSE, row.names = T)


## citizenship ##

levels(prosNEW$Citizenship.status)
```

```
## [1] "Foreign national"            "Residing in U.S. as refugee"
## [3] "Residing in U.S. on visa"    "U.S. citizen"
## [5] "U.S. permanent resident"     "Unknown"
```

```r
tab <- table(prosNEW$Citizenship.status, prosNEW$Period)
tab[1,] <- tab[1,] + tab[2,] + tab[3,]
tab[2,] <- tab[4,] + tab[5,]
tab <- tab[c(1,2),]
rownames(tab) <- c("Foreign National", "Citizen")

# Chi sq
chisq.test(tab)
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
##
##  Pearson's Chi-squared test
##
## data:  tab
## X-squared = 150.47, df = 11, p-value < 2.2e-16
```

```r
chisq.test(tab)$expected  #<5's
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
##
##                            1         2        3        4         5
##   Foreign National  6.371409  42.66074 25.48564 114.6854  55.68057
##   Citizen          16.628591 111.33926 66.51436 299.3146 145.31943
##
##                            6        7         8        9      10        11
##   Foreign National  57.89672 11.91176  39.33653 1.662107 27.9788 19.11423
```

```
##   Citizen          151.10328 31.08824 102.66347 4.337893 73.0212 49.88577
##
##                          12
##   Foreign National 2.216142
##   Citizen          5.783858
```

```r
#Cramer's V
sqrt(chisq.test(tab)$statistic/(sum(tab) * (min(nrow(tab), ncol(tab)) - 1)))
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
## X-squared
## 0.3208097
```

```r
# Fisher
fisher.test(tab, simulate.p.value = T, B=2000) #Monte carlo sims
```

```
##
##  Fisher's Exact Test for Count Data with simulated p-value (based
##  on 2000 replicates)
##
## data:  tab
## p-value = 0.0004998
## alternative hypothesis: two.sided
```

```r
# column proportions
for (j in 1:ncol(tab)){
  c <- as.numeric(tab[,j])
  b <- sum(c)
  for (i in 1:nrow(tab)){
    a <- as.numeric(tab[i,j])
    prop <- a/b
    tab[i,j] <- paste(a, round(prop,2), sep="; ")
  }
}

write.table(tab, file = "tab7.txt", sep = ",", quote = FALSE, row.names = T)

## jurisdiction ##

levels(prosNEW$Jurisdiction)
```

```
## [1] "#"        "Federal"  "Federal " "State"    "State "
```

```r
Clean <- prosNEW %>%
  filter(Jurisdiction != "#")

tab <- table(Clean$Jurisdiction, Clean$Period)
```

```r
tab[2,] <- tab[2,] + tab[3,]
tab[1,] <- tab[4,] + tab[5,]
tab <- tab[c(1,2),]
rownames(tab) <- c("State", "Federal")

# Chi sq
chisq.test(tab)
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect

##
##  Pearson's Chi-squared test
##
## data:  tab
## X-squared = 106.54, df = 11, p-value < 2.2e-16
```

```r
chisq.test(tab)$expected  #<5's
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect

##
##                   1         2        3         4        5         6
##   State    3.606675  16.72186 10.27356  48.96335  22.4051  23.49804
##   Federal 29.393325 136.27814 83.72644 399.03665 182.5949 191.50196
##
##                   7         8         9        10        11        12
##   State    4.699607  15.84751 0.6557592 11.91296  7.54123 0.8743455
##   Federal 38.300393 129.15249 5.3442408 97.08704 61.45877 7.1256545
```

```r
#Cramer's V
sqrt(chisq.test(tab)$statistic/(sum(tab) * (min(nrow(tab), ncol(tab)) - 1)))
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect

## X-squared
## 0.2640519
```

```r
# Fisher
fisher.test(tab, simulate.p.value = T, B=2000) #Monte carlo sims
```

```
##
##  Fisher's Exact Test for Count Data with simulated p-value (based
##  on 2000 replicates)
##
## data:  tab
## p-value = 0.0004998
## alternative hypothesis: two.sided
```

```r
# column proportions
for (j in 1:ncol(tab)){
  c <- as.numeric(tab[,j])
  b <- sum(c)
  for (i in 1:nrow(tab)){
    a <- as.numeric(tab[i,j])
    prop <- a/b
    tab[i,j] <- paste(a, round(prop,2), sep="; ")
  }
}

write.table(tab, file = "tab8.txt", sep = ",", quote = FALSE, row.names = T)

## plea ##

levels(prosNEW$Plea)
```

```
## [1] "Charged but not tried"            "DATA NOT FOUND"
## [3] "Guilty: plea bargain/blind plea" "No contest"
## [5] "Not guilty: blind plea"           "Not guilty: special defense"
## [7] "Pending"                          "Unknown"
```

```r
tab <- table(prosNEW$Plea, prosNEW$Period)
tab[1,] <- tab[1,] + tab[7,]
tab[2,] <- tab[5,] + tab[6, ]
tab <- tab[c(1,2,3),]
rownames(tab) <- c("Charged", "Not Guilty", "Guilty")

# Chi sq
chisq.test(tab)
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect

##
##  Pearson's Chi-squared test
##
## data:  tab
## X-squared = 164.55, df = 22, p-value < 2.2e-16
```

```r
chisq.test(tab)$expected  #<5's
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect

##
##                     1        2        3         4        5        6
##   Charged    3.954270 20.29859 12.39005  58.12777 26.36180 26.36180
##   Not Guilty 7.706792 39.56153 24.14795 113.28985 51.37861 51.37861
```

```
##   Guilty     18.338937 94.13988 57.46200 269.58238 122.25958 122.25958
##
##                      7        8         9        10        11        12
##   Charged     5.27236 18.45326 0.7908541 14.10356  8.831204 1.054472
##   Not Guilty 10.27572 35.96503 1.5413584 27.48756 17.211836 2.055145
##   Guilty     24.45192 85.58171 3.6677875 65.40888 40.956960 4.890383
```

```r
#Cramer's V
sqrt(chisq.test(tab)$statistic/(sum(tab) * (min(nrow(tab), ncol(tab)) - 1)))
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
## X-squared
## 0.2352258
```

```r
# Fisher
fisher.test(tab, simulate.p.value = T, B=2000) #Monte carlo sims
```

```
##
##  Fisher's Exact Test for Count Data with simulated p-value (based
##  on 2000 replicates)
##
## data:  tab
## p-value = 0.0004998
## alternative hypothesis: two.sided
```

```r
# column proportions
for (j in 1:ncol(tab)){
  c <- as.numeric(tab[,j])
  b <- sum(c)
  for (i in 1:nrow(tab)){
    a <- as.numeric(tab[i,j])
    prop <- a/b
    tab[i,j] <- paste(a, round(prop,2), sep="; ")
  }
}

write.table(tab, file = "tab9.txt", sep = ",", quote = FALSE, row.names = T)

## verdict ##

levels(prosNEW$Verdict)
```

```
## [1] "Charged but not tried"
## [2] "Guilty"
## [3] "Guilty "
## [4] "Guilty on some charges/not guilty on others"
```

```
## [5] "Hung jury/mistrial"
## [6] "Not guilty"
## [7] "Pending"
## [8] "Unknown"
```

```
Clean <- prosNEW %>%
  filter(Verdict != "CHECK PACER")

tab <- table(Clean$Verdict, Clean$Period)
tab[1,] <- tab[1,] + tab[8,]
tab[2,] <- tab[3,] + tab[4,] + tab[5,]
tab[3,] <- tab[7,]
tab <- tab[c(1,2,3),]
rownames(tab) <- c("Charged", "Guilty", "Not Guilty")

# Chi sq
chisq.test(tab)
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect

##
##  Pearson's Chi-squared test
##
## data:  tab
## X-squared = NaN, df = 22, p-value = NA
```

```
chisq.test(tab)$expected  #<5's
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect

##
##                     1        2         3         4         5        6
##   Charged    1.9136691 6.219424 12.917266 31.575540 15.787770 20.57194
##   Guilty     0.5755396 1.870504  3.884892  9.496403  4.748201  6.18705
##   Not Guilty 1.5107914 4.910072 10.197842 24.928058 12.464029 16.24101
##
##                     7         8 9        10        11        12
##   Charged    1.9136691 10.046763 0 14.352518 15.787770 1.9136691
##   Guilty     0.5755396  3.021583 0  4.316547  4.748201 0.5755396
##   Not Guilty 1.5107914  7.931655 0 11.330935 12.464029 1.5107914
```

```
#Cramer's V
sqrt(chisq.test(tab)$statistic/(sum(tab) * (min(nrow(tab), ncol(tab)) - 1)))
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect

## X-squared
##       NaN
```

```r
# Fisher
fisher.test(tab, simulate.p.value = T, B=2000) #Monte carlo sims
```

```
##
##  Fisher's Exact Test for Count Data with simulated p-value (based
##  on 2000 replicates)
##
## data:  tab
## p-value = 0.0004998
## alternative hypothesis: two.sided
```

```r
# column proportions
for (j in 1:ncol(tab)){
  c <- as.numeric(tab[,j])
  b <- sum(c)
  for (i in 1:nrow(tab)){
    a <- as.numeric(tab[i,j])
    prop <- a/b
    tab[i,j] <- paste(a, round(prop,2), sep="; ")
  }
}

write.table(tab, file = "tab10.txt", sep = ",", quote = FALSE, row.names = T)


## length of sentence ##

levels(prosNEW$Length.of.prison.sentence)
```

```
##   [1] "#"                "0"                "1"                "10"
##   [5] "100"              "102"              "1020"             "1032"
##   [9] "108"              "1080"             "11"               "110"
##  [13] "111"              "112"              "114"              "117"
##  [17] "1188"             "12"               "12.5"             "120"
##  [21] "121"              "126"              "130"              "132"
##  [25] "1320"             "135"              "136"              "137"
##  [29] "138"              "14"               "140"              "144"
##  [33] "1440"             "15"               "150"              "150.96"
##  [37] "151"              "152"              "156"              "1560"
##  [41] "16"               "160"              "161"              "162"
##  [45] "166"              "168"              "1680"             "1692"
##  [49] "17"               "17.5"             "170"              "18"
##  [53] "180"              "181"              "182"              "1860"
##  [57] "188"              "192"              "1920"             "194"
##  [61] "195"              "2"                "2.5"              "20"
```

```
##  [65] "204"          "21"           "210"          "216"
##  [69] "22"           "220"          "23"           "234"
##  [73] "235"          "24"           "240"          "243"
##  [77] "249"          "25"           "252"          "255"
##  [81] "258"          "262"          "264"          "266"
##  [85] "27"           "270"          "272"          "276"
##  [89] "28"           "288"          "2880"         "29"
##  [93] "292"          "294"          "3"            "3.25"
##  [97] "30"           "300"          "31"           "312"
## [101] "32"           "324"          "33"           "336"
## [105] "34"           "348"          "36"           "360"
## [109] "363"          "364"          "37"           "378"
## [113] "3788"         "384"          "396"          "4"
## [117] "4.17"         "4.3"          "4.5"          "40"
## [121] "400"          "402"          "405"          "41"
## [125] "41.5"         "42"           "42.5"         "420"
## [129] "432"          "438"          "44"           "444"
## [133] "45"           "450"          "46"           "468"
## [137] "48"           "480"          "4816"         "5"
## [141] "5.5"          "50"           "51"           "516"
## [145] "52"           "54"           "540"          "55"
## [149] "56"           "564"          "57"           "576"
## [153] "58"           "6"            "60"           "600"
## [157] "61"           "63"           "648"          "65"
## [161] "66"           "660"          "684"          "69"
## [165] "7"            "7.67"         "70"           "71"
## [169] "72"           "720"          "729"          "74"
## [173] "75"           "77"           "78"           "780"
## [177] "79"           "8"            "80"           "82"
## [181] "84"           "87"           "88"           "9"
## [185] "90"           "92"           "95"           "96"
## [189] "97"           "98"           "DATA NOT FOUND" "Pending"
## [193] "x"            "X"
```

```r
Clean <- prosNEW %>%
  filter(Verdict != "CHECK PACER" | Verdict != "Pending") %>%
  mutate(Length.Sentence = cut(as.numeric(as.character(Length.of.prison.sentence)), c(0
  filter(is.na(Length.Sentence) == F)
```

```
## Warning in cut(as.numeric(as.character(Length.of.prison.sentence)), c(0, :
## NAs introduced by coercion
```

```r
tab <- table(Clean$Length.Sentence, Clean$Period)

# Chi sq
chisq.test(tab)
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect

##
##  Pearson's Chi-squared test
##
## data:  tab
## X-squared = 107.01, df = 44, p-value = 3.624e-07
```

```r
chisq.test(tab)$expected  #<5's
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect

##
##                     1         2         3          4         5         6
##   (0,100]   8.6635220 58.334382 27.723270 174.425577 79.704403 76.816562
##   (100,200] 3.4905660 23.503145 11.169811  70.276730 32.113208 30.949686
##   (200,300] 1.7295597 11.645702  5.534591  34.821803 15.911950 15.335430
##   (300,400] 0.6761006  4.552411  2.163522  13.612159  6.220126  5.994759
##   (400,500] 0.4402516  2.964361  1.408805   8.863732  4.050314  3.903564
##
##                     7         8         9        10         11          12
##   (0,100]   16.749476 58.334382 2.8878407 28.878407 17.3270440 1.15513627
##   (100,200]  6.748428 23.503145 1.1635220 11.635220  6.9811321 0.46540881
##   (200,300]  3.343816 11.645702 0.5765199  5.765199  3.4591195 0.23060797
##   (300,400]  1.307128  4.552411 0.2253669  2.253669  1.3522013 0.09014675
##   (400,500]  0.851153  2.964361 0.1467505  1.467505  0.8805031 0.05870021
```

```r
#Cramer's V
sqrt(chisq.test(tab)$statistic/(sum(tab) * (min(nrow(tab), ncol(tab)) - 1)))
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect

## X-squared
## 0.1674616
```

```r
# Fisher
fisher.test(tab, simulate.p.value = T, B=2000) #Monte carlo sims
```

```
##
##  Fisher's Exact Test for Count Data with simulated p-value (based
##  on 2000 replicates)
##
## data:  tab
## p-value = 0.0004998
## alternative hypothesis: two.sided
```

```r
# column proportions
for (j in 1:ncol(tab)){
  c <- as.numeric(tab[,j])
```

```
  b <- sum(c)
  for (i in 1:nrow(tab)){
    a <- as.numeric(tab[i,j])
    prop <- a/b
    tab[i,j] <- paste(a, round(prop,2), sep="; ")
  }
}

tab <- summary(as.numeric(as.character(Clean$Length.of.prison.sentence)), na.rm=T)

#write.table(tab, file = "tab11.txt", sep = ",", quote = FALSE, row.names = T)

## death sentence ##

levels(prosNEW$Death.sentence)
```

```
## [1] "#"                "0"                "1"                "DATA NOT FOUND"
## [5] "Peding"           "Pending"
```

```
tab <- table(Clean$Death.sentence, Clean$Period)
tab <- tab[c(2,3),]

# Chi sq
chisq.test(tab) ##FAIL TO REJECT, A LOT OF ZEROS
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
##
##  Pearson's Chi-squared test
##
## data:  tab
## X-squared = 4.327, df = 11, p-value = 0.9594
```

```
chisq.test(tab)$expected  #<5's
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
##
##              1         2         3           4           5          6
##   0 14.96855346 100.78826 47.8993711 301.3668763 137.7106918 132.721174
##   1  0.03144654   0.21174  0.1006289   0.6331237   0.2893082   0.278826
##
##              7         8          9          10          11          12
##   0 28.93920335 100.78826 4.98951782 49.8951782 29.93710692 1.995807128
##   1  0.06079665   0.21174 0.01048218  0.1048218  0.06289308 0.004192872
```

```r
#Cramer's V
sqrt(chisq.test(tab)$statistic/(sum(tab) * (min(nrow(tab), ncol(tab)) - 1)))
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
##  X-squared
## 0.06734678
```

```r
# Fisher
fisher.test(tab, simulate.p.value = T, B=2000) #Monte carlo sims
```

```
##
##  Fisher's Exact Test for Count Data with simulated p-value (based
##  on 2000 replicates)
##
## data:  tab
## p-value = 1
## alternative hypothesis: two.sided
```

```r
# column proportions
for (j in 1:ncol(tab)){
  c <- as.numeric(tab[,j])
  b <- sum(c)
  for (i in 1:nrow(tab)){
    a <- as.numeric(tab[i,j])
    prop <- a/b
    tab[i,j] <- paste(a, round(prop,2), sep="; ")
  }
}

write.table(tab, file = "tab12.txt", sep = ",", quote = FALSE, row.names = T)

## Ideology ##

levels(prosNEW$Ideological.affiliation)
```

```
##  [1] "Leftist: eco-animal focused"  "Leftist: government-focused"
##  [3] "Leftist: identity-focused"    "Nationalist-separatist"
##  [5] "No affiliation/not a factor"  "Other"
##  [7] "Rightist: abortion-focused"   "Rightist: government-focused"
##  [9] "Rightist: identity-focused"   "Rightist: unspecified"
## [11] "Salafi/Jihadist/Islamist"     "Unclear"
```

```r
tab <- table(Clean$Ideological.affiliation, Clean$Period)
tab[1,] <- tab[1,] + tab[2,] + tab[3,]
tab[2,] <- tab[7,] + tab[8,] + tab[9,] + tab[10,]
tab[3,] <- tab[5,] + tab[6,] + tab[12,]
```

```r
tab[5,] <- tab[11,]
tab <- tab[c(1:5),]
rownames(tab) <- c("Leftist", "Rightist", "Other", "Nationalist-Separatist", "Salafi/Jih

# Chi sq
chisq.test(tab)
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
##
##  Pearson's Chi-squared test
##
## data:  tab
## X-squared = 328.75, df = 44, p-value < 2.2e-16
```

```r
chisq.test(tab)$expected  #<5's
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
##
##                                  1         2         3         4
##   Leftist                1.8553459 12.492662  5.937107  37.35430
##   Rightist               4.4339623 29.855346 14.188679  89.27044
##   Other                  2.3270440 15.668763  7.446541  46.85115
##   Nationalist-Separatist 0.5031447  3.387841  1.610063  10.12998
##   Salafi/Jihadist/Islamist 5.8805031 39.595388 18.817610 118.39413
##
##                                  5         6          7         8
##   Leftist                17.069182 16.450734  3.5870021 12.492662
##   Rightist               40.792453 39.314465  8.5723270 29.855346
##   Other                  21.408805 20.633124  4.4989518 15.668763
##   Nationalist-Separatist  4.628931  4.461216  0.9727463  3.387841
##   Salafi/Jihadist/Islamist 54.100629 52.140461 11.3689727 39.595388
##
##                                  9        10        11         12
##   Leftist                0.6184486  6.184486  3.710692 0.24737945
##   Rightist               1.4779874 14.779874  8.867925 0.59119497
##   Other                  0.7756813  7.756813  4.654088 0.31027254
##   Nationalist-Separatist 0.1677149  1.677149  1.006289 0.06708595
##   Salafi/Jihadist/Islamist 1.9601677 19.601677 11.761006 0.78406709
```

```r
#Cramer's V
sqrt(chisq.test(tab)$statistic/(sum(tab) * (min(nrow(tab), ncol(tab)) - 1)))
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
## X-squared
```

```
## 0.2935131
```

```r
# Fisher
fisher.test(tab, simulate.p.value = T, B=2000) #Monte carlo sims
```

```
##
##  Fisher's Exact Test for Count Data with simulated p-value (based
##  on 2000 replicates)
##
## data:  tab
## p-value = 0.0004998
## alternative hypothesis: two.sided
```

```r
# column proportions
for (j in 1:ncol(tab)){
  c <- as.numeric(tab[,j])
  b <- sum(c)
  for (i in 1:nrow(tab)){
    a <- as.numeric(tab[i,j])
    prop <- a/b
    tab[i,j] <- paste(a, round(prop,2), sep="; ")
  }
}

write.table(tab, file = "tab13.txt", sep = ",", quote = FALSE, row.names = T)

## Tactic ##

Clean <- prosNEW %>%
  filter(Tactic != "#")

tab <- table(Clean$Tactic, Clean$Period)
#tab[21,] <- tab[19,] + tab[12,] + tab[21,] + tab[17,] + tab[1,] + tab[5,]
#tab <- tab[c(15, 9, 20, 3,  10, 12, 14, 2, 11, 4, 6, 8, 21),]
#rownames(tab)[nrow(tab)] <- "Unarmed Assault"

# Chi sq
chisq.test(tab)
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect

##
##  Pearson's Chi-squared test
##
## data:  tab
## X-squared = 1420.4, df = 209, p-value < 2.2e-16
```

```r
chisq.test(tab)$expected  #<5's
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect

##
##                                                                         1
##   Animal release                                               0.10777270
##   Armed intimidation/standoff                                  0.94839974
##   Arson                                                        2.52188112
##   Blade or blunt weapon                                        0.25865447
##   Blockading                                                   0.04310908
##   Bomb threat/hoax                                             0.04310908
##   Chemical or biological weapon deployment                     0.25865447
##   Criminal violation not linked or motivated politically       3.23318093
##   Explosives                                                   5.30241672
##   Firearms: civilian                                           2.41410843
##   Firearms: military                                           0.30176355
##   Hostage-taking                                               1.12083605
##   Other                                                        0.15088178
##   Perjury/obstruction of justice                               1.01306336
##   Providing material/financial support to terrorist organization 9.85042456
##   Unarmed assault                                              0.12932724
##   Unknown/unspecified/undeveloped                              0.90529066
##   Vandalism/sabotage                                           0.17243632
##   Various methods                                              4.07380797
##   Vehicle ramming                                              0.15088178
##
##                                                                         2
##   Animal release                                                0.5029393
##   Armed intimidation/standoff                                   4.4258654
##   Arson                                                        11.7687786
##   Blade or blunt weapon                                         1.2070542
##   Blockading                                                    0.2011757
##   Bomb threat/hoax                                              0.2011757
##   Chemical or biological weapon deployment                      1.2070542
##   Criminal violation not linked or motivated politically       15.0881777
##   Explosives                                                   24.7446114
##   Firearms: civilian                                           11.2658393
##   Firearms: military                                            1.4082299
##   Hostage-taking                                                5.2305683
##   Other                                                         0.7041150
##   Perjury/obstruction of justice                                4.7276290
##   Providing material/financial support to terrorist organization 45.9686479
##   Unarmed assault                                               0.6035271
##   Unknown/unspecified/undeveloped                               4.2246897
```

```
##   Vandalism/sabotage                                               0.8047028
##   Various methods                                                 19.0111039
##   Vehicle ramming                                                  0.7041150
##
##                                                                            3
##   Animal release                                                   0.3069889
##   Armed intimidation/standoff                                      2.7015023
##   Arson                                                            7.1835402
##   Blade or blunt weapon                                            0.7367734
##   Blockading                                                       0.1227956
##   Bomb threat/hoax                                                 0.1227956
##   Chemical or biological weapon deployment                         0.7367734
##   Criminal violation not linked or motivated politically           9.2096669
##   Explosives                                                      15.1038537
##   Firearms: civilian                                               6.8765513
##   Firearms: military                                               0.8595689
##   Hostage-taking                                                   3.1926845
##   Other                                                            0.4297845
##   Perjury/obstruction of justice                                   2.8856956
##   Providing material/financial support to terrorist organization 28.0587851
##   Unarmed assault                                                  0.3683867
##   Unknown/unspecified/undeveloped                                  2.5787067
##   Vandalism/sabotage                                               0.4911822
##   Various methods                                                 11.6041803
##   Vehicle ramming                                                  0.4297845
##
##                                                                             4
##   Animal release                                                    1.4696277
##   Armed intimidation/standoff                                      12.9327237
##   Arson                                                            34.3892880
##   Blade or blunt weapon                                             3.5271065
##   Blockading                                                        0.5878511
##   Bomb threat/hoax                                                  0.5878511
##   Chemical or biological weapon deployment                          3.5271065
##   Criminal violation not linked or motivated politically           44.0888308
##   Explosives                                                       72.3056826
##   Firearms: civilian                                               32.9196604
##   Firearms: military                                                4.1149575
##   Hostage-taking                                                   15.2841280
##   Other                                                             2.0574788
##   Perjury/obstruction of justice                                   13.8145003
##   Providing material/financial support to terrorist organization 134.3239713
##   Unarmed assault                                                   1.7635532
##   Unknown/unspecified/undeveloped                                  12.3448726
##   Vandalism/sabotage                                                2.3514043
```

```
## Various methods                                             55.5519268
## Vehicle ramming                                              2.0574788
##
##                                                                      5
## Animal release                                               0.6694971
## Armed intimidation/standoff                                  5.8915741
## Arson                                                       15.6662312
## Blade or blunt weapon                                        1.6067929
## Blockading                                                   0.2677988
## Bomb threat/hoax                                             0.2677988
## Chemical or biological weapon deployment                     1.6067929
## Criminal violation not linked or motivated politically      20.0849118
## Explosives                                                  32.9392554
## Firearms: civilian                                          14.9967342
## Firearms: military                                           1.8745918
## Hostage-taking                                               6.9627694
## Other                                                        0.9372959
## Perjury/obstruction of justice                               6.2932724
## Providing material/financial support to terrorist organization 61.1920314
## Unarmed assault                                              0.8033965
## Unknown/unspecified/undeveloped                              5.6237753
## Vandalism/sabotage                                           1.0711953
## Various methods                                             25.3069889
## Vehicle ramming                                              0.9372959
##
##                                                                      6
## Animal release                                               0.7021555
## Armed intimidation/standoff                                  6.1789680
## Arson                                                       16.4304376
## Blade or blunt weapon                                        1.6851731
## Blockading                                                   0.2808622
## Bomb threat/hoax                                             0.2808622
## Chemical or biological weapon deployment                     1.6851731
## Criminal violation not linked or motivated politically      21.0646636
## Explosives                                                  34.5460483
## Firearms: civilian                                          15.7282822
## Firearms: military                                           1.9660353
## Hostage-taking                                               7.3024167
## Other                                                        0.9830176
## Perjury/obstruction of justice                               6.6002613
## Providing material/financial support to terrorist organization 64.1770085
## Unarmed assault                                              0.8425865
## Unknown/unspecified/undeveloped                              5.8981058
## Vandalism/sabotage                                           1.1234487
## Various methods                                             26.5414762
```

```
##   Vehicle ramming                                          0.9830176
##
##                                                                   7
##   Animal release                                           0.14043109
##   Armed intimidation/standoff                              1.23579360
##   Arson                                                    3.28608752
##   Blade or blunt weapon                                    0.33703462
##   Blockading                                               0.05617244
##   Bomb threat/hoax                                         0.05617244
##   Chemical or biological weapon deployment                 0.33703462
##   Criminal violation not linked or motivated politically   4.21293272
##   Explosives                                               6.90920967
##   Firearms: civilian                                       3.14565643
##   Firearms: military                                       0.39320705
##   Hostage-taking                                           1.46048334
##   Other                                                    0.19660353
##   Perjury/obstruction of justice                           1.32005225
##   Providing material/financial support to terrorist organization 12.83540170
##   Unarmed assault                                          0.16851731
##   Unknown/unspecified/undeveloped                          1.17962116
##   Vandalism/sabotage                                       0.22468975
##   Various methods                                          5.30829523
##   Vehicle ramming                                          0.19660353
##
##                                                                   8
##   Animal release                                           0.4735467
##   Armed intimidation/standoff                              4.1672110
##   Arson                                                   11.0809928
##   Blade or blunt weapon                                    1.1365121
##   Blockading                                               0.1894187
##   Bomb threat/hoax                                         0.1894187
##   Chemical or biological weapon deployment                 1.1365121
##   Criminal violation not linked or motivated politically  14.2064010
##   Explosives                                              23.2984977
##   Firearms: civilian                                      10.6074461
##   Firearms: military                                       1.3259308
##   Hostage-taking                                           4.9248857
##   Other                                                    0.6629654
##   Perjury/obstruction of justice                           4.4513390
##   Providing material/financial support to terrorist organization 43.2821685
##   Unarmed assault                                          0.5682560
##   Unknown/unspecified/undeveloped                          3.9777923
##   Vandalism/sabotage                                       0.7576747
##   Various methods                                         17.9000653
##   Vehicle ramming                                          0.6629654
```

```
##
##                                                                          9
##   Animal release                                               0.019595036
##   Armed intimidation/standoff                                  0.172436316
##   Arson                                                        0.458523841
##   Blade or blunt weapon                                        0.047028086
##   Blockading                                                   0.007838014
##   Bomb threat/hoax                                             0.007838014
##   Chemical or biological weapon deployment                     0.047028086
##   Criminal violation not linked or motivated politically       0.587851078
##   Explosives                                                   0.964075767
##   Firearms: civilian                                           0.438928805
##   Firearms: military                                           0.054866101
##   Hostage-taking                                               0.203788374
##   Other                                                        0.027433050
##   Perjury/obstruction of justice                               0.184193338
##   Providing material/financial support to terrorist organization 1.790986283
##   Unarmed assault                                              0.023514043
##   Unknown/unspecified/undeveloped                              0.164598302
##   Vandalism/sabotage                                           0.031352057
##   Various methods                                              0.740692358
##   Vehicle ramming                                              0.027433050
##
##                                                                         10
##   Animal release                                                 0.3559765
##   Armed intimidation/standoff                                    3.1325931
##   Arson                                                          8.3298498
##   Blade or blunt weapon                                          0.8543436
##   Blockading                                                     0.1423906
##   Bomb threat/hoax                                               0.1423906
##   Chemical or biological weapon deployment                       0.8543436
##   Criminal violation not linked or motivated politically        10.6792946
##   Explosives                                                    17.5140431
##   Firearms: civilian                                             7.9738733
##   Firearms: military                                             0.9967342
##   Hostage-taking                                                 3.7021555
##   Other                                                          0.4983671
##   Perjury/obstruction of justice                                 3.3461790
##   Providing material/financial support to terrorist organization 32.5362508
##   Unarmed assault                                                0.4271718
##   Unknown/unspecified/undeveloped                                2.9902025
##   Vandalism/sabotage                                             0.5695624
##   Various methods                                               13.4559112
##   Vehicle ramming                                                0.4983671
##
```

```
##                                                                    11
##   Animal release                                                    0.22534291
##   Armed intimidation/standoff                                       1.98301764
##   Arson                                                             5.27302417
##   Blade or blunt weapon                                             0.54082299
##   Blockading                                                        0.09013717
##   Bomb threat/hoax                                                  0.09013717
##   Chemical or biological weapon deployment                          0.54082299
##   Criminal violation not linked or motivated politically            6.76028739
##   Explosives                                                       11.08687133
##   Firearms: civilian                                                5.04768125
##   Firearms: military                                                0.63096016
##   Hostage-taking                                                    2.34356630
##   Other                                                             0.31548008
##   Perjury/obstruction of justice                                    2.11822338
##   Providing material/financial support to terrorist organization 20.59634226
##   Unarmed assault                                                   0.27041150
##   Unknown/unspecified/undeveloped                                   1.89288047
##   Vandalism/sabotage                                                0.36054866
##   Various methods                                                   8.51796212
##   Vehicle ramming                                                   0.31548008
##
##                                                                   12
##   Animal release                                                 0.02612671
##   Armed intimidation/standoff                                    0.22991509
##   Arson                                                          0.61136512
##   Blade or blunt weapon                                          0.06270411
##   Blockading                                                     0.01045069
##   Bomb threat/hoax                                               0.01045069
##   Chemical or biological weapon deployment                       0.06270411
##   Criminal violation not linked or motivated politically         0.78380144
##   Explosives                                                     1.28543436
##   Firearms: civilian                                             0.58523841
##   Firearms: military                                             0.07315480
##   Hostage-taking                                                 0.27171783
##   Other                                                          0.03657740
##   Perjury/obstruction of justice                                 0.24559112
##   Providing material/financial support to terrorist organization 2.38798171
##   Unarmed assault                                                0.03135206
##   Unknown/unspecified/undeveloped                                0.21946440
##   Vandalism/sabotage                                             0.04180274
##   Various methods                                                0.98758981
##   Vehicle ramming                                                0.03657740
```

```r
#Cramer's V
sqrt(chisq.test(tab)$statistic/(sum(tab) * (min(nrow(tab), ncol(tab)) - 1)))
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
## X-squared
## 0.2904211
```

```r
# Fisher
fisher.test(tab, simulate.p.value = T, B=2000) #Monte carlo sims
```

```
##
##  Fisher's Exact Test for Count Data with simulated p-value (based
##  on 2000 replicates)
##
## data:  tab
## p-value = 0.0004998
## alternative hypothesis: two.sided
```

```r
# column proportions
for (j in 1:ncol(tab)){
  c <- as.numeric(tab[,j])
  b <- sum(c)
  for (i in 1:nrow(tab)){
    a <- as.numeric(tab[i,j])
    prop <- a/b
    tab[i,j] <- paste(a, round(prop,2), sep="; ")
  }
}

write.table(tab, file = "tab14.txt", sep = ",", quote = FALSE, row.names = T)


## Physical Target ##

levels(prosNEW$Physical.target)
```

```
##  [1] "Educational institution"
##  [2] "Federal site: judicial"
##  [3] "Federal site: military"
##  [4] "Federal site: non-military non-judicial"
##  [5] "Federal site: non-U.S. embassy or consulate"
##  [6] "Individual person(s)"
##  [7] "Mass transportation: air"
##  [8] "Mass transportation: ground"
##  [9] "Mass transportation: infrastructure"
```

```
## [10] "Mass transportation: water"
## [11] "Medical institution"
## [12] "Multiple types"
## [13] "Municipal: local law enforcement"
## [14] "No direct target"
## [15] "Online"
## [16] "Private site: business/corporate property"
## [17] "Private site: residential"
## [18] "Public site: event"
## [19] "Public: commercial space of recreation"
## [20] "Public: non-commercial space"
## [21] "Religious institution"
## [22] "State site: judicial"
## [23] "State site: non-military non-judicial"
## [24] "Unspecified/unknown/undeveloped"
## [25] "Unspecified/unknown/undeveloped "
```

```
tab <- table(prosNEW$Physical.target, prosNEW$Period)
tab[1,] <- tab[1,] + tab[11,] + tab[15,] + tab[18,] + tab[19,] + tab[20,]
tab[2,] <- tab[2,] + tab[3,] + tab[4,] + tab[5,]
tab[3,] <- tab[12,] + tab[22,] + tab[23,]
tab[4,] <- tab[7,] + tab[8,] + tab[9,] + tab[10,]
tab[5,] <- tab[16,] + tab[17,]
tab <- tab[1:5,]
rownames(tab) <- c("Public", "Federal", "State", "Mass Transportation", "Private")

# Chi sq
chisq.test(tab)
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
##
##  Pearson's Chi-squared test
##
## data:  tab
## X-squared = 191.73, df = 44, p-value < 2.2e-16
```

```
chisq.test(tab)$expected  #<5's
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
##
##                              1        2         3        4         5
##   Public              6.487013 27.38961 13.214286 24.26623 17.298701
##   Federal             6.837662 28.87013 13.928571 25.57792 18.233766
##   State               4.426948 18.69156  9.017857 16.56006 11.805195
##   Mass Transportation 2.717532 11.47403  5.535714 10.16558  7.246753
```

```
##   Private              6.530844 27.57468 13.303571 24.43019 17.415584
##
##                                6        7         8         9        10
##   Public              19.701299 6.487013 10.571429 0.4805195 15.857143
##   Federal             20.766234 6.837662 11.142857 0.5064935 16.714286
##   State               13.444805 4.426948  7.214286 0.3279221 10.821429
##   Mass Transportation  8.253247 2.717532  4.428571 0.2012987  6.642857
##   Private             19.834416 6.530844 10.642857 0.4837662 15.964286
##
##                              11        12
##   Public              5.285714 0.9610390
##   Federal             5.571429 1.0129870
##   State               3.607143 0.6558442
##   Mass Transportation 2.214286 0.4025974
##   Private             5.321429 0.9675325
```

```r
#Cramer's V
sqrt(chisq.test(tab)$statistic/(sum(tab) * (min(nrow(tab), ncol(tab)) - 1)))
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
## X-squared
## 0.2789461
```

```r
# Fisher
fisher.test(tab, simulate.p.value = T, B=2000) #Monte carlo sims
```

```
##
##  Fisher's Exact Test for Count Data with simulated p-value (based
##  on 2000 replicates)
##
## data:  tab
## p-value = 0.0004998
## alternative hypothesis: two.sided
```

```r
# column proportions
for (j in 1:ncol(tab)){
  c <- as.numeric(tab[,j])
  b <- sum(c)
  for (i in 1:nrow(tab)){
    a <- as.numeric(tab[i,j])
    prop <- a/b
    tab[i,j] <- paste(a, round(prop,2), sep="; ")
  }
}

write.table(tab, file = "tab15.txt", sep = ",", quote = FALSE, row.names = T)
```

```
## Ideological Target ##

levels(prosNEW$Ideological.target)
```

```
##  [1] "General public"
##  [2] "Government: federal"
##  [3] "Government: first responders"
##  [4] "Government: foreign/non-U.S."
##  [5] "Government: international"
##  [6] "Government: military"
##  [7] "Government: police"
##  [8] "Government: state"
##  [9] "Identity: nationality"
## [10] "Identity: political affiliation"
## [11] "Identity: race/ethnicity"
## [12] "Identity: sexuality"
## [13] "Industry: abortion"
## [14] "Industry: adult entertainment"
## [15] "Industry: animal products/food/research"
## [16] "Industry: land development"
## [17] "Industry: place of attacker's employment"
## [18] "Industry: private corporations"
## [19] "Industry: technology/research"
## [20] "Multiple motivations"
## [21] "Religious: Christian"
## [22] "Religious: Jewish"
## [23] "Religious: Jewish "
## [24] "Religious: Muslim"
## [25] "Religious: other"
## [26] "Unspecified"
## [27] "Unspecified "
```

```
# column proportions
tab <- table(prosNEW$Ideological.target, prosNEW$Period)
tab[1,] <- tab[20,] + tab[26,] + tab[27,]
tab[2,] <- tab[2,] + tab[3,] + tab[4,] + tab[5,] + tab[6,] + tab[7,] + tab[8,]
tab[3,] <- tab[9,] + tab[10,] + tab[11,] + tab[12,]
tab[4,] <- tab[13,] + tab[14,] + tab[15,] + tab[16,] + tab[17,] + tab[18,] + tab[19,]
tab[5,] <- tab[21,] + tab[22,] + tab[23,] + tab[24,] + tab[25,]
tab <- tab[1:5,]
rownames(tab) <- c("Public", "Government", "Identity", "Industry", "Religious")

# Chi sq
chisq.test(tab)
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect

##
##  Pearson's Chi-squared test
##
## data:  tab
## X-squared = 386.3, df = 44, p-value < 2.2e-16
```

```r
chisq.test(tab)$expected  #<5's
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect

##
##                    1         2         3         4        5          6
##   Public     14.911989 75.074151 43.707554 221.62301 99.75606 101.298683
##   Government  7.656965 38.548857 22.442827 113.79834 51.22245  52.014553
##   Identity    2.411642 12.141372  7.068607  35.84200 16.13306  16.382536
##   Industry    2.793486 14.063756  8.187803  41.51698 18.68746  18.976438
##   Religious   1.225918  6.171864  3.593209  18.21968  8.20097   8.327789
##
##                    7         8         9        10        11         12
##   Public     21.082467 71.474705 2.0568261 53.991684 33.423423 3.5994456
##   Government 10.825364 36.700624 1.0561331 27.723493 17.162162 1.8482328
##   Identity    3.409563 11.559252 0.3326403  8.731809  5.405405 0.5821206
##   Industry    3.949411 13.389466 0.3853084 10.114345  6.261261 0.6742897
##   Religious   1.733195  5.875953 0.1690922  4.438669  2.747748 0.2959113
```

```r
#Cramer's V
sqrt(chisq.test(tab)$statistic/(sum(tab) * (min(nrow(tab), ncol(tab)) - 1)))
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect

## X-squared
## 0.2587022
```

```r
# Fisher
fisher.test(tab, simulate.p.value = T, B=2000)
```

```
##
##  Fisher's Exact Test for Count Data with simulated p-value (based
##  on 2000 replicates)
##
## data:  tab
## p-value = 0.0004998
## alternative hypothesis: two.sided
```

```r
for (j in 1:ncol(tab)){
  c <- as.numeric(tab[,j])
  b <- sum(c)
```

```
  for (i in 1:nrow(tab)){
    a <- as.numeric(tab[i,j])
    prop <- a/b
    tab[i,j] <- paste(a, round(prop,2), sep="; ")
  }
}

write.table(tab, file = "tab16.txt", sep = ",", quote = FALSE, row.names = T)

## Informant ##

levels(prosNEW$Informant)
```

```
## [1] "No"                           "Presumed but not documented"
## [3] "Unknown"                      "Yes"
```

```
tab <- table(prosNEW$Informant, prosNEW$Period)
tab <- tab[c(-2,-3),]

# Chi sq
chisq.test(tab)
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
##
##  Pearson's Chi-squared test
##
## data:  tab
## X-squared = 37.944, df = 11, p-value = 7.996e-05
```

```
chisq.test(tab)$expected  #<5's
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
##
##              1        2        3       4         5         6        7
##   No  20.65499 96.38995 58.83543 281.033 125.80767 128.93721 25.66226
##   Yes 12.34501 57.61005 35.16457 167.967  75.19233  77.06279 15.33774
##
##              8        9       10      11      12
##   No  90.13087 3.755453 68.22406 42.5618 5.00727
##   Yes 53.86913 2.244547 40.77594 25.4382 2.99273
```

```
#Cramer's V
sqrt(chisq.test(tab)$statistic/(sum(tab) * (min(nrow(tab), ncol(tab)) - 1)))
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
## X-squared
## 0.1583621
```

```
# Fisher
fisher.test(tab, simulate.p.value = T, B=2000)
```

```
##
##  Fisher's Exact Test for Count Data with simulated p-value (based
##  on 2000 replicates)
##
## data:  tab
## p-value = 0.0004998
## alternative hypothesis: two.sided
```

```
# column proportions
for (j in 1:ncol(tab)){
  c <- as.numeric(tab[,j])
  b <- sum(c)
  for (i in 1:nrow(tab)){
    a <- as.numeric(tab[i,j])
    prop <- a/b
    tab[i,j] <- paste(a, round(prop,2), sep="; ")
  }
}

write.table(tab, file = "tab17.txt", sep = ",", quote = FALSE, row.names = T)


## Group affiliation ##

levels(prosNEW$Group.affiliation)
```

```
##   [1] "\"survivalist groups\""
##   [2] "Abu Sayyaf Group"
##   [3] "al-Fuqra"
##   [4] "al-Gama'a al-Islamiyya"
##   [5] "al-Nusrah Front"
##   [6] "Al Qaeda (AQ)"
##   [7] "Al Qaeda (AQ), Al Qaeda in the Arabian Peninsula (AQAP)"
##   [8] "Al Qaeda (AQ), Al Shabab"
##   [9] "Al Qaeda (AQ), Revolutionary Armed Forces of Colombia (FARC)"
##  [10] "Al Qaeda (AQ), Taliban"
##  [11] "Al Qaeda (AQ), Taliban, Mujahedeen"
##  [12] "Al Shabab"
##  [13] "Alabama Free Miltia "
##  [14] "Alaska Peacemaker Militia (APM)"
```

```
## [15] "Alaska Peacemakers Militia (APM)"
## [16] "Alt-Reich"
## [17] "American Front"
## [18] "American Insurgent Movement"
## [19] "American Nationalist Brotherhood"
## [20] "Animal Liberation Front (ALF)"
## [21] "Anonymous"
## [22] "Ansar al-Sharia (AAS)"
## [23] "Ansar al-Sharia; UBJ"
## [24] "Armed Islamic Group in Algeria"
## [25] "Army of God (AOG)"
## [26] "Aryan Brotherhood"
## [27] "Aryan Nations (AN)"
## [28] "Aryan Republican Army (ARA)"
## [29] "Aryan Strike Force"
## [30] "Asatruist"
## [31] "AtomWaffen"
## [32] "Austin Affinity Group"
## [33] "Black Snake Militia"
## [34] "Blood and Honour Arkansas"
## [35] "Brookville Tiger Militia"
## [36] "Cambodian Freedom Fighters (CFF)"
## [37] "Colorado First Light Infantry"
## [38] "Earth Liberation Front (ELF)"
## [39] "Family Farm Preservation"
## [40] "Forever Enduring Always Ready (FEAR)"
## [41] "Free Papuan Movement (OPM)"
## [42] "Freedom Club (FC)"
## [43] "Frente Revolucionario Boricua"
## [44] "Government of Free Vietnam"
## [45] "Guardians of the Free Republic"
## [46] "Help the Needy"
## [47] "Hizballah"
## [48] "Holy Land Foundation"
## [49] "Hope Pregnancy Ministries"
## [50] "Hutaree"
## [51] "Idaho Mountain Boys Militia Group"
## [52] "Irish Republican Army (IRA)"
## [53] "ISILIslamic State (IS/ISIL/ISIS)"
## [54] "Islamic Assembly of North America, Al-Haramain Islamic Foundation, Dar Al-asr,
## [55] "Islamic Committee for Palestine, Islamic Concern Project"
## [56] "Islamic Jihad Union (IJU)"
## [57] "Islamic Movement of Uzbekistan"
## [58] "Islamic State (IS/ISIL/ISIS)"
## [59] "Islamic State (IS/ISIL/ISIS), Free Syrian Army, al-Nusrah Front, Ahrar al-Sham
```

```
##  [60] "Jaish-e-Mohammad"
##  [61] "Jamâ\200\231iyyat Ul-Islam Is-Saheeh"
##  [62] "Jamaâ\200\231ah al-Islamiyah"
##  [63] "Jamaâ\200\231at al-Fuqra (FUQRA)"
##  [64] "Japanese Red Army"
##  [65] "Jemaah Islamiya (JI)"
##  [66] "Jemaah Islamiyah (JI)"
##  [67] "Jewish Defense League (JDL)"
##  [68] "Jural Society"
##  [69] "Justice Commandos of the Armenian Genocide (JCAG)"
##  [70] "Kansas Militia"
##  [71] "Kentucky State Militia"
##  [72] "Khalistan Commando Force (KCF)"
##  [73] "Klu Klux Klan (KKK)"
##  [74] "Ku Klux Klan (KKK)"
##  [75] "Lambs of Christ"
##  [76] "Lashka-E-Taiba (LeT)"
##  [77] "Lashkar-e-Taiba (LeT), Harakat-ul-Jihad-Islami"
##  [78] "Mara Salvatrucha (MS-13)"
##  [79] "Michigan Militia Corps Wolverine"
##  [80] "Militia At Large for the Republic of Georgia/116th Georgia Militia"
##  [81] "Minutemen Militia "
##  [82] "Montana Freemen"
##  [83] "Montana Freemen "
##  [84] "Moorish National Republic"
##  [85] "Mountaineer Militia"
##  [86] "Mujahedeen"
##  [87] "Multiple"
##  [88] "National Alliance (NA)"
##  [89] "National Knights of the Klu Klux Klan"
##  [90] "National Socialist Movement (NSM)"
##  [91] "National Socialist Movement (NSM), Aryan Liberation Movement"
##  [92] "New World Order (NWO)"
##  [93] "No affiliation"
##  [94] "North American Militia of Southwestern Michigan"
##  [95] "Oath Keepers"
##  [96] "Oklahoma Constitutional Militia (OCM)"
##  [97] "Pakistani Taliban"
##  [98] "Palestinian Islamic Jihad (PIJ)"
##  [99] "Patriots Defense Force Militia"
## [100] "Phineas Priesthood"
## [101] "Project 7"
## [102] "Quds Force"
## [103] "Republic of Texas (ROT)"
## [104] "Respect the Flag"
```

```
## [105] "Revolutionary Armed Forces of Colombia (FARC)"
## [106] "Revolutionary Armed Forces of Columbia (FARC)"
## [107] "Salafist Group for Call and Combat (GSPC)"
## [108] "San Joaquin Militia"
## [109] "Seperatist Republic of Texas, Sovereign Citizens"
## [110] "Silent Aryan Warriors"
## [111] "Silent Resistance Army"
## [112] "Sons of Liberty"
## [113] "South Carolina Militia, \"private militia groups\""
## [114] "South Carolina Minutemen Corps"
## [115] "Southeastern States Alliance"
## [116] "Sovereign Citizens Movement"
## [117] "Sovereign Movement"
## [118] "Sovereign Movement "
## [119] "Stop Huntingdon Animal Cruelty (SHAC)"
## [120] "Supreme White Alliance (SWA)"
## [121] "Taliban"
## [122] "Taliban, Al Qaeda (AQ), Hezb-e-Islami Gulbuddin (HIG)"
## [123] "Taliban, Chechen Mujahideen"
## [124] "Tamil Tigers (LTTE)"
## [125] "Tea Party "
## [126] "Texas Militia and Combined Action Program (TMCAP)"
## [127] "The Hated"
## [128] "The Islamic Resistance Movement (HAMAS)"
## [129] "The Islamic Resistance Movement (HAMAS), Al Qaeda (AQ)"
## [130] "The RNC Welcoming Committee"
## [131] "Three Percenters, Six Delta"
## [132] "Toronto 18"
## [133] "Tunisian Jihadists"
## [134] "Ummah \"The Brotherhood\""
## [135] "United Aryan Empire"
## [136] "United Self Defense Forces of Colombia (AUC)"
## [137] "United Self Defense Forces of Columbia (AUC)"
## [138] "Unknown"
## [139] "Valhalla Bound Skinheads, Vanguard Kindred"
## [140] "Viper Militia"
## [141] "Virginia Jihad Network"
## [142] "Washington State Militia"
## [143] "White Church Supremacists (The White Church)"
## [144] "World Church of the Creator (WCOTC)"
## [145] "XXX Minutemen Militia"
```

```r
Clean <- prosNEW %>% group_by(Group.affiliation) %>%
  summarize(count = n()) %>%
  filter(count > 20) %>%
```

```r
  arrange(-count) %>%
  mutate(Group.affiliation = factor(Group.affiliation))

Clean2 <- prosNEW %>% filter(Group.affiliation %in% Clean$Group.affiliation) %>%
  mutate(Group.affiliation = factor(Group.affiliation))

tab <- table(Clean2$Group.affiliation, Clean2$Period)

# Chi sq
chisq.test(tab) ### HUGE TABLE, CRAZY 0's
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
##
##  Pearson's Chi-squared test
##
## data:  tab
## X-squared = 1045.6, df = 110, p-value < 2.2e-16
```

```r
chisq.test(tab)$expected  #<5's
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
##
##                                                       1         2
##   Al Qaeda (AQ)                                2.5060241  8.927711
##   Al Shabab                                    0.8303985  2.958295
##   Animal Liberation Front (ALF)                0.3410565  1.215014
##   Earth Liberation Front (ELF)                 0.4596849  1.637627
##   Hizballah                                    1.3938832  4.965709
##   Islamic State (IS/ISIL/ISIS)                 1.6163114  5.758109
##   Multiple                                     0.5783133  2.060241
##   No affiliation                               6.7469880 24.036145
##   Revolutionary Armed Forces of Columbia (FARC) 0.8748842  3.116775
##   Taliban                                      0.3113994  1.109361
##   The Islamic Resistance Movement (HAMAS)      0.3410565  1.215014
##
##                                                        3          4
##   Al Qaeda (AQ)                                11.277108  54.192771
##   Al Shabab                                     3.736793  17.957368
##   Animal Liberation Front (ALF)                 1.534754   7.375348
##   Earth Liberation Front (ELF)                  2.068582   9.940686
##   Hizballah                                     6.272475  30.142725
##   Islamic State (IS/ISIL/ISIS)                  7.273401  34.952734
##   Multiple                                      2.602410  12.506024
##   No affiliation                               30.361446 145.903614
```

```
##   Revolutionary Armed Forces of Columbia (FARC)  3.936979  18.919370
##   Taliban                                        1.401297   6.734013
##   The Islamic Resistance Movement (HAMAS)        1.534754   7.375348
##
##                                                         5         6
##   Al Qaeda (AQ)                                 22.240964 22.710843
##   Al Shabab                                      7.369787  7.525487
##   Animal Liberation Front (ALF)                  3.026877  3.090825
##   Earth Liberation Front (ELF)                   4.079703  4.165894
##   Hizballah                                     12.370714 12.632067
##   Islamic State (IS/ISIL/ISIS)                  14.344764 14.647822
##   Multiple                                       5.132530  5.240964
##   No affiliation                                59.879518 61.144578
##   Revolutionary Armed Forces of Columbia (FARC)  7.764597  7.928638
##   Taliban                                        2.763670  2.822057
##   The Islamic Resistance Movement (HAMAS)        3.026877  3.090825
##
##                                                          7         8
##   Al Qaeda (AQ)                                  4.8554217 17.698795
##   Al Shabab                                      1.6088971  5.864690
##   Animal Liberation Front (ALF)                  0.6607970  2.408712
##   Earth Liberation Front (ELF)                   0.8906395  3.246525
##   Hizballah                                      2.7006487  9.844300
##   Islamic State (IS/ISIL/ISIS)                   3.1316033 11.415199
##   Multiple                                       1.1204819  4.084337
##   No affiliation                                13.0722892 47.650602
##   Revolutionary Armed Forces of Columbia (FARC)  1.6950880  6.178869
##   Taliban                                        0.6033364  2.199259
##   The Islamic Resistance Movement (HAMAS)        0.6607970  2.408712
##
##                                                          9        10
##   Al Qaeda (AQ)                                 0.78313253 13.469880
##   Al Shabab                                     0.25949954  4.463392
##   Animal Liberation Front (ALF)                 0.10658017  1.833179
##   Earth Liberation Front (ELF)                  0.14365153  2.470806
##   Hizballah                                     0.43558851  7.492122
##   Islamic State (IS/ISIL/ISIS)                  0.50509731  8.687674
##   Multiple                                      0.18072289  3.108434
##   No affiliation                                2.10843373 36.265060
##   Revolutionary Armed Forces of Columbia (FARC) 0.27340130  4.702502
##   Taliban                                       0.09731233  1.673772
##   The Islamic Resistance Movement (HAMAS)       0.10658017  1.833179
##
##                                                       11        12
##   Al Qaeda (AQ)                                  9.240964 1.0963855
```

```
##   Al Shabab                                   3.062095 0.3632994
##   Animal Liberation Front (ALF)               1.257646 0.1492122
##   Earth Liberation Front (ELF)                1.695088 0.2011121
##   Hizballah                                   5.139944 0.6098239
##   Islamic State (IS/ISIL/ISIS)                5.960148 0.7071362
##   Multiple                                    2.132530 0.2530120
##   No affiliation                             24.879518 2.9518072
##   Revolutionary Armed Forces of Columbia (FARC)  3.226135 0.3827618
##   Taliban                                     1.148285 0.1362373
##   The Islamic Resistance Movement (HAMAS)     1.257646 0.1492122
```

```
#Cramer's V
sqrt(chisq.test(tab)$statistic/(sum(tab) * (min(nrow(tab), ncol(tab)) - 1)))
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
## X-squared
## 0.3112927
```

```
# Fisher
fisher.test(tab, simulate.p.value = T, B=2000)
```

```
##
##  Fisher's Exact Test for Count Data with simulated p-value (based
##  on 2000 replicates)
##
## data:  tab
## p-value = 0.0004998
## alternative hypothesis: two.sided
```

```
# column proportions
for (j in 1:ncol(tab)){
  c <- as.numeric(tab[,j])
  b <- sum(c)
  for (i in 1:nrow(tab)){
    a <- as.numeric(tab[i,j])
    prop <- a/b
    tab[i,j] <- paste(a, round(prop,2), sep="; ")
  }
}

write.table(tab, file = "tab18.txt", sep = ",", quote = FALSE, row.names = T)


## FTO affiliation ##

levels(prosNEW$Affiliation.with.FTO)
```

```
## [1] "No"      "Unknown" "Yes"     "Yes "
```

```r
tab <- table(prosNEW$Affiliation.with.FTO, prosNEW$Period)
tab[3,] <- tab[3,] + tab[4,]
tab <- tab[c(1,3),]

# Chi sq
chisq.test(tab)
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
##
##  Pearson's Chi-squared test
##
## data:  tab
## X-squared = 149.1, df = 11, p-value < 2.2e-16
```

```r
chisq.test(tab)$expected  #<5's
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
##
##              1        2        3        4         5         6        7
##   No  17.68089 82.51083 50.36376 237.8884 109.83585 114.65791 23.03874
##   Yes 15.31911 71.48917 43.63624 206.1116  95.16415  99.34209 19.96126
##
##              8        9       10       11       12
##   No  77.68877 3.214708 58.40053 36.43336 4.286277
##   Yes 67.31123 2.785292 50.59947 31.56664 3.713723
```

```r
#Cramer's V
sqrt(chisq.test(tab)$statistic/(sum(tab) * (min(nrow(tab), ncol(tab)) - 1)))
```

```
## Warning in chisq.test(tab): Chi-squared approximation may be incorrect
```

```
## X-squared
## 0.3128899
```

```r
# Fisher
fisher.test(tab, simulate.p.value = T, B=2000)
```

```
##
##  Fisher's Exact Test for Count Data with simulated p-value (based
##  on 2000 replicates)
##
## data:  tab
## p-value = 0.0004998
## alternative hypothesis: two.sided
```

```
# column proportions
for (j in 1:ncol(tab)){
  c <- as.numeric(tab[,j])
  b <- sum(c)
  for (i in 1:nrow(tab)){
    a <- as.numeric(tab[i,j])
    prop <- a/b
    tab[i,j] <- paste(a, round(prop,2), sep="; ")
  }
}

write.table(tab, file = "tab19.txt", sep = ",", quote = FALSE, row.names = T)

#################################################################################
# # Three Way Table                                                             #
# # Here, we compute three CMH tests comparing:                                 #
#  # Ethnicity vs Sentence Length vs Time                                       #
#  # Ethnicity vs Plea vs Time                                                  #
#  # Ethnicity vs Tactic vs Time                                                #
#                                                                               #
# # Further down, we create a graphic for Ethnicity vs Tactic vs Time comparison #
#                                                                               #
#################################################################################

# Ethnicity vs Sentence Length vs Time data
Clean <- prosNEW %>%
  mutate(Length.Sentence = cut(as.numeric(as.character(Length.of.prison.sentence)), c(0
  filter(is.na(Length.Sentence) == F) %>%
  filter(!(Racial.ethnic.group %in% c("American Indian/Alaska Native", "Unknown", "Birac
  mutate(Racial.ethnic.group = factor(Racial.ethnic.group))
```

```
## Warning in cut(as.numeric(as.character(Length.of.prison.sentence)), c(0, :
## NAs introduced by coercion
```

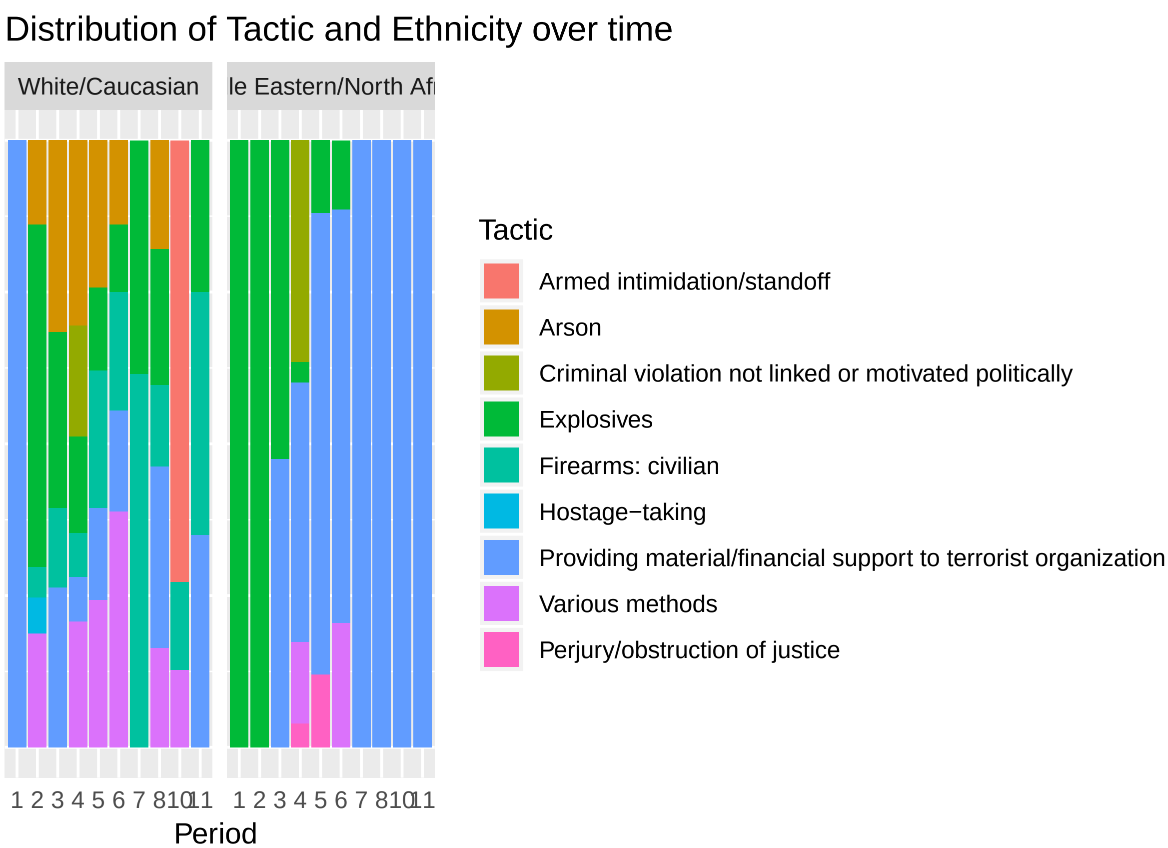
```
# Ethnicity vs Plea vs Time data
Clean2 <- prosNEW %>%
  filter(!(Racial.ethnic.group %in% c("American Indian/Alaska Native", "Unknown", "Birac
  mutate(Racial.ethnic.group = factor(Racial.ethnic.group)) %>%
  mutate(Plea = ifelse(Plea=="Pending", "Charged but not tried", ifelse(
    Plea %in% c("Not guilty: blind plea", "Not guilty: special defense"), "Not Guilty",
      Plea=="Guilty: plea bargain/blind plea", "Guilty", Plea)))) %>%
  filter(Plea %in% c("Charged but not tried", "Not Guilty", "Guilty")) %>%
  mutate(Plea = factor(Plea))

# Ethnicity vs Tactic vs Time data
```

```r
Clean3 <- prosNEW %>%
  group_by(Tactic) %>%
  summarize(count = n()) %>%
  filter(count > 10) %>%
  arrange(-count) %>%
  filter(Tactic != "Unknown/unspecified/undeveloped")
Clean4 <- prosNEW %>%
  filter(Tactic %in% Clean3$Tactic) %>%
  filter(!(Racial.ethnic.group %in% c("American Indian/Alaska Native", "Birac
  mutate(Racial.ethnic.group = factor(Racial.ethnic.group), Tactic= factor(Tactic))

# Creating the tables

# Ethnicity vs Sentence Length vs Time table
tab.3  <- table(Clean$Racial.ethnic.group, Clean$Length.Sentence, Clean$Period)

# Ethnicity vs Plea vs Time table
tab.3  <- table(Clean2$Racial.ethnic.group, Clean2$Plea, Clean2$Period)

# Ethnicity vs Tactic vs Time table
tab.3  <- table(Clean4$Racial.ethnic.group, Clean4$Tactic, Clean4$Period)

# CMH Test
mantelhaen.test(tab.3)
```

```
##
##  Cochran-Mantel-Haenszel test
##
## data:  tab.3
## Cochran-Mantel-Haenszel M^2 = 532.24, df = 44, p-value < 2.2e-16
```

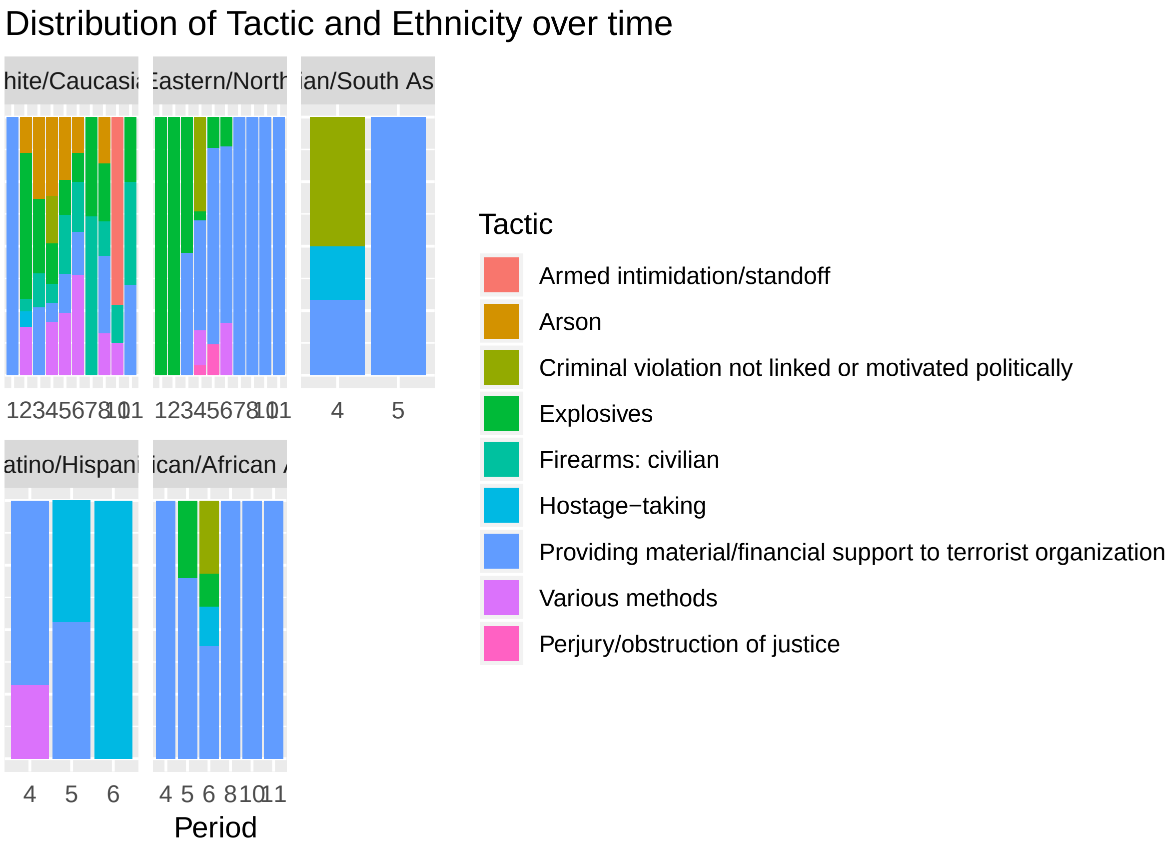
```r
# Exporting contingency table
write.table(tab.3, file = "3tab.txt", sep = ",", quote = FALSE, row.names = T)


# Plotting Ethnicity vs Tactic vs Time
  # We remove low counts from the charts
  # Just middle eastern and white groups

tab.3_plot <- as.data.frame(tab.3)
colnames(tab.3_plot) <- c("Ethnicity", "Tactic", "Period", "Freq")

tab.3_plot2 <- tab.3_plot %>% filter(Ethnicity == "White/Caucasian") %>%
  filter(Freq > 4) %>%
  mutate(Ethnicity = factor(Ethnicity), Tactic = factor(Tactic))
```

```
tab.3_plot3 <- tab.3_plot %>% filter(Ethnicity =="Middle Eastern/North African" ) %>%
  filter(Freq > 4) %>%
  mutate(Ethnicity = factor(Ethnicity), Tactic = factor(Tactic))

tab.3_plot4 <- rbind(tab.3_plot2, tab.3_plot3)

ggplot() +
  geom_bar(aes(x=Period, y=Freq, fill=Tactic),size=2, stat="identity", position="fill",
  labs(x = "Period ", y="", title="Distribution of Tactic and Ethnicity over time") +
  facet_wrap(Ethnicity~., scales="free_x") +
  theme(axis.text.y = element_blank(), axis.ticks= element_blank())
```




```
# All ethnicities

tab.3_plot <- as.data.frame(tab.3)
colnames(tab.3_plot) <- c("Ethnicity", "Tactic", "Period", "Freq")

tab.3_plot2 <- tab.3_plot %>% filter(Ethnicity == "White/Caucasian") %>%
  filter(Freq > 4) %>%
  mutate(Ethnicity = factor(Ethnicity), Tactic = factor(Tactic))
```

```r
tab.3_plot3 <- tab.3_plot %>% filter(Ethnicity =="Middle Eastern/North African" ) %>%
  filter(Freq > 4) %>%
  mutate(Ethnicity = factor(Ethnicity), Tactic = factor(Tactic))

tab.3_plot4 <- tab.3_plot %>% filter(Ethnicity =="Asian/South Asian" ) %>%
  filter(Freq > 4) %>%
  mutate(Ethnicity = factor(Ethnicity), Tactic = factor(Tactic))

tab.3_plot5 <- tab.3_plot %>% filter(Ethnicity =="Latino/Hispanic" ) %>%
  filter(Freq > 4) %>%
  mutate(Ethnicity = factor(Ethnicity), Tactic = factor(Tactic))

tab.3_plot6 <- tab.3_plot %>% filter(Ethnicity == "Black/African/African American" ) %>%
  filter(Freq > 4) %>%
  mutate(Ethnicity = factor(Ethnicity), Tactic = factor(Tactic))

tab.3_plotf <- rbind(tab.3_plot2, tab.3_plot3, tab.3_plot4, tab.3_plot5, tab.3_plot6)


ggplot() +
  geom_bar(aes(x=Period, y=Freq, fill=Tactic),size=2, stat="identity", position="fill",
  labs(x = "Period ", y="", title="Distribution of Tactic and Ethnicity over time") +
  facet_wrap(Ethnicity~., scales="free_x") +
  theme(axis.text.y = element_blank(), axis.ticks= element_blank())
```


Distribution of Tactic and Ethnicity over time
hite/Caucasi
Eastern/North
ian/South As
atino/Hispani
ican/African
Period
Tactic
Armed intimidation/standoff
Arson
Criminal violation not linked or motivated politically
Explosives
Firearms: civilian
Hostage−taking
Providing material/financial support to terrorist organization
Various methods
Perjury/obstruction of justice