Impaired Driving Special IMPACT Study

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Data Comparisons: FY2017 vw FY2015-2016
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Table of Contents

Introduction

This document presents the results of a comparison of ID crashes compared to non-ID crashes over a recent three year period (FY2015-2017). An over-represented value of an attribute is a situation found where that attribute has a greater share of ID crashes than would be expected if it were the same as that same attribute in non-ID crashes. That is, the non-ID crashes are serving as a control to which the ID crashes are being compared. In this way anything different about ID crashes surfaces and can be subjected to further analyses.

[Fiscal years (FY) are defined to be the last three months of the previous calendar year coupled with the first 9 months of the nominal calendar year; for example, FY2017 consists of October-December of 2016 plus January-September of 2017.]

The analytical technique employed to generate most of the displays below is called Information Mining Performance Analysis Control Technique (IMPACT). For a detailed description of the meaning of each element of the IMPACT outputs, see:

http://www.caps.ua.edu/software/care/

The first section below will compare FY2017 ID crashes against FY2015-2016 ID crashes to determine any significant changes that have occurred in FY2017 from the previous two fiscal years. After this, the comparison between ID and non-ID crashes will be presented under the following headings:

- Geographic Factors
- Time Factors
- Factors Affecting Severity
- Driver and Vehicle Demographics

A summary of findings is given after these analyses are presented.

Impaired Driving (ID) Update for FY2017

This section will compare ID crashes that occurred in FY2017 with those that occurred in the previous two fiscal years (FY2015-2016). The goal of this comparison is to surface factors that have undergone a significant change in the FY2017 time frame. A comparison by severity gives the highest level overview.

Overall Crashes by Year

Before getting into the ID subset, it is good to get a feel for the overall difference in the crash frequencies over the past fiscal years. The following table gives a monthly comparison of total crashes over the three fiscal years. Please realize that the October, November and December months are from the previous calendar years despite their being shown in the normal monthly sequence.

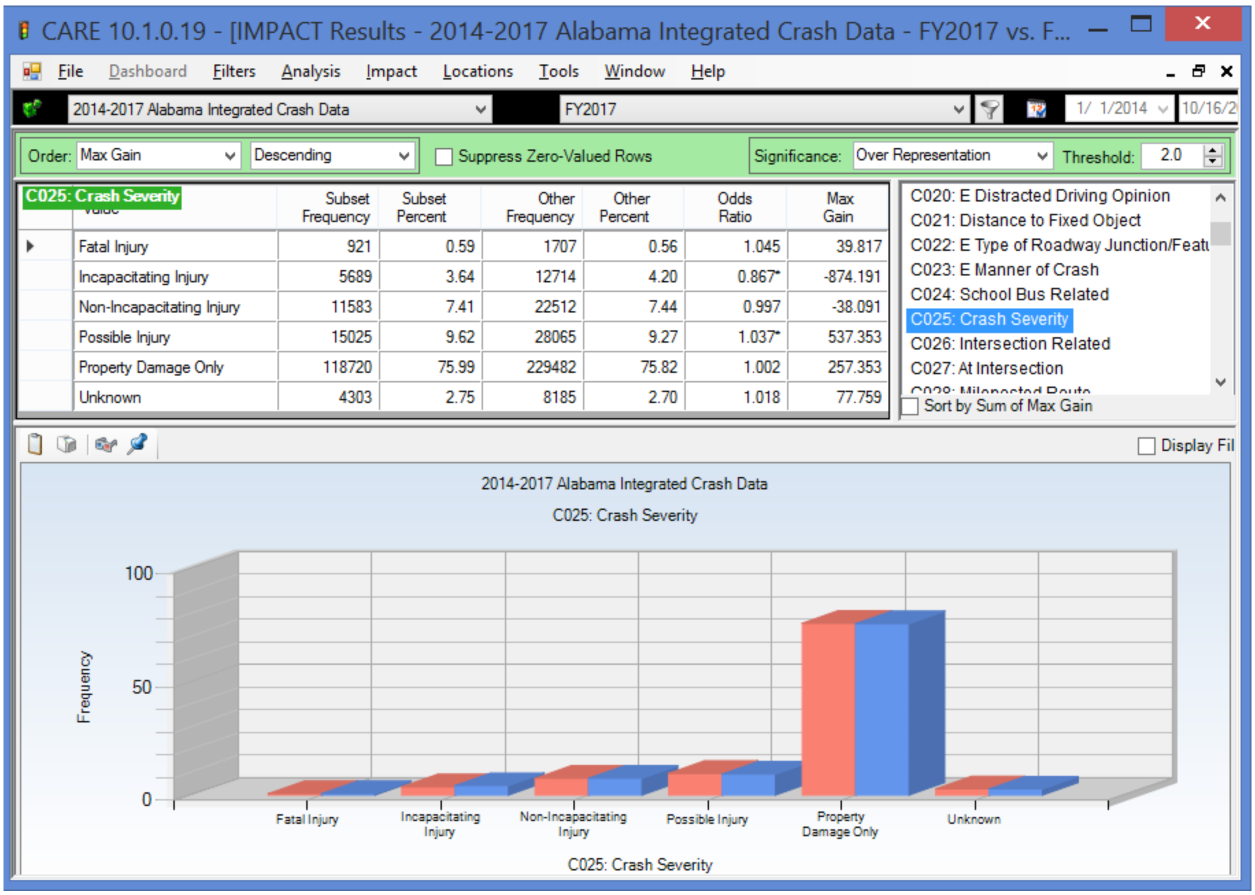
Crashes by Month for Fiscal Years 2015-2017

	FY2015	FY2016	FY2017	TOTAL
January	11362	12135	12251	35748
February	10939	12557	11878	35374
March	12295	13764	13497	39556
April	12836	13327	13115	39278
May	12525	12822	13857	39204
June	11201	12204	13522	36927
July	11963	12498	12096	36557
August	12698	13861	13275	39834
September	12333	12916	12540	37789
October	12403	14034	13647	40084
November	11755	13228	12938	37921
December	12554	14455	13625	40634
TOTAL	**144864**	**157801**	**156241**	**458906**
Percent	31.57%	34.39%	34.05%	100.00%

We conclude from considering the percentage numbers at the bottom of the table that FY2017 was not significantly different in total crashes from FY2016, there being only a 0.31% difference. However, it is clear from looking at the low percent in FY2015, as well as the numbers themselves, that there as a significant increase from FY2015 to FY2016. This reflects the general findings with regard to dramatic increase in CY2016, and it does not appear that there has been a large regression to the mean in the first 9 months of CY2017 to overcome this increase. With regard to interpreting the remainder of the findings, we should view FY2017 as quite comparable in number to FY2016, and thus, retaining the increase over FY2015. However, we shall see that the frequency of fatal crashes was significantly lower in FY2017, and that a major factor in this reduction was the reduction in the ID fatal crashes.

Overall Severity Comparisons

The following presents a comparison of the severities of crashes in FY2017 against those of FY2015-2016. In the table above the chart the Subset Frequency and Percent is for FY2017, which the Other Frequency and Percent is for the previous two fiscal years, and thus the order of magnitude of the frequencies is about double that of FY2017. Comparisons must be against the percentages to determine if there is a trend direction being set in increased or decreased severity for these crashes.



C025: Crash Severity	Subset Frequency	Subset Percent	Other Frequency	Other Percent	Odds Ratio	Max Gain
Fatal Injury	921	0.59	1707	0.56	1.045	39.817
Incapacitating Injury	5689	3.64	12714	4.20	0.867*	-874.191
Non-Incapacitating Injury	11583	7.41	22512	7.44	0.997	-38.091
Possible Injury	15025	9.62	28065	9.27	1.037*	537.353
Property Damage Only	118720	75.99	229482	75.82	1.002	257.353
Unknown	4303	2.75	8185	2.70	1.018	77.759

The increase in the proportion of the number of fatal injuries (0.03%) is not significant recognizing that the comparisons take into account the differences in overall crashes. It is a 4.5% increase in the proportions, which are quite small for the overall fatality crash rate per crash. The difference in the average of the two before years is 853.5, which makes a difference in FY2017 of an increase of 67.5 fatal crashes.

In the other injury severities, there is a significant decrease in the Incapacitating Injury and a significant increase in the Possible Injury. This difference tends to balance out the increase in the fatal crashes, since quite often the characteristics of an incapacitating injury crash are not at all different from that crash being fatal. Thus, this reduction should be seen as quite favorable. The difference in Non-Incapacitating Injury is not seen to be significant.

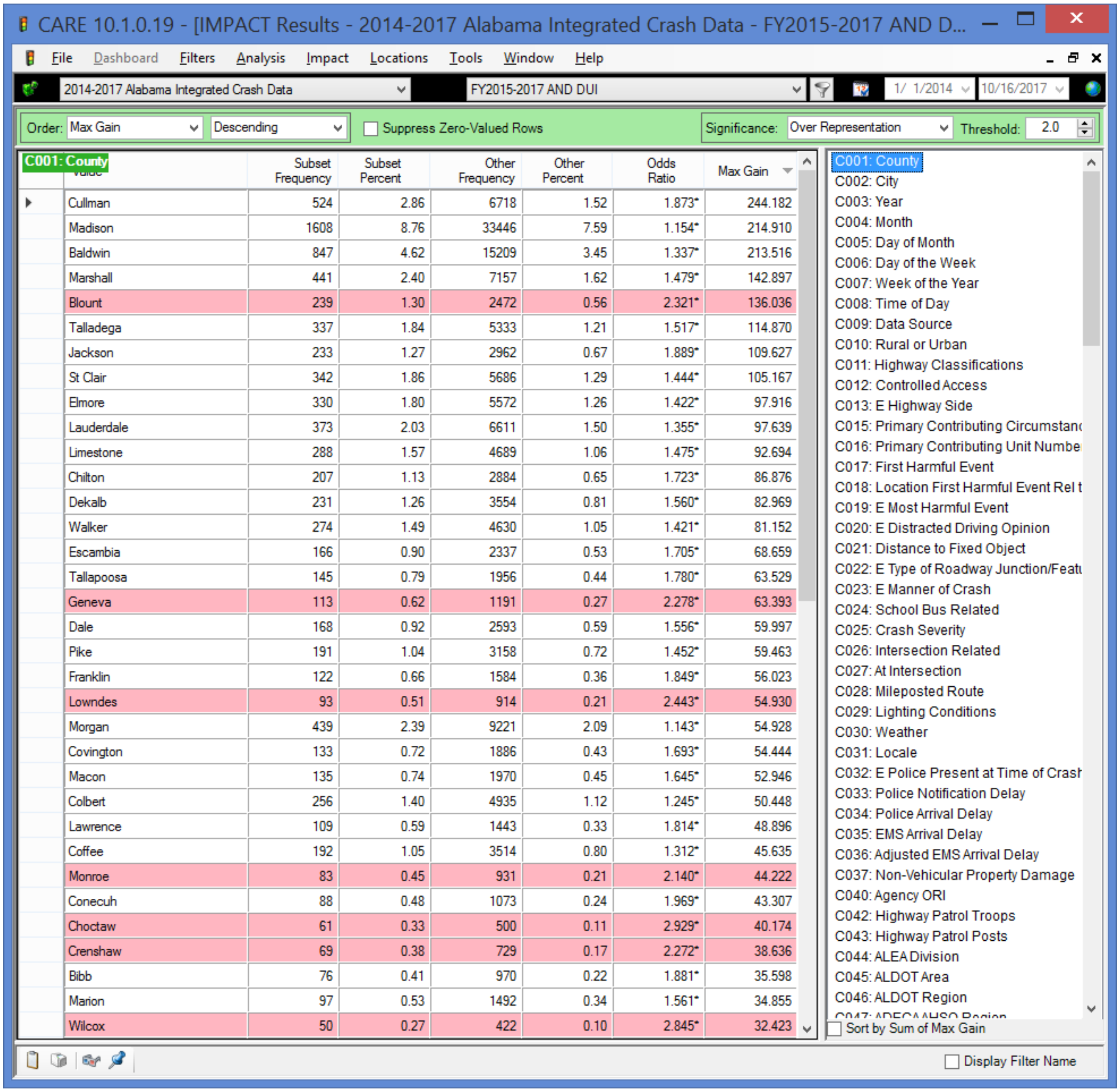
Considering fatal crashes by individual years, the totals for the three years are given in the table below for all crashes and for ID crashes.

	FY2015	**FY2016**	**% Over FY2015**	**FY2017**	**% Over FY2016**
All Fatal Crashes	766	941	22.8%	921	-2.1%
ID Fatal Crashes	207	226	9.2%	188	-16.8%
ID % of all Fatal	27.0%	24.0%	-	20.4%	-

Clearly there is a significant trend away from reported ID being the cause of fatal crashes. This should be taken into consideration in the interpretation of the findings regarding the various attributes that are given in the remainder of this problem identification. The increase in overall fatalities from FY2015 to FY2016 was 22.8%, and this decrease was only 2.1% in FY2017. Similarly, the ID fatal crashes had a 9.2% increase and a 1.7% decrease.

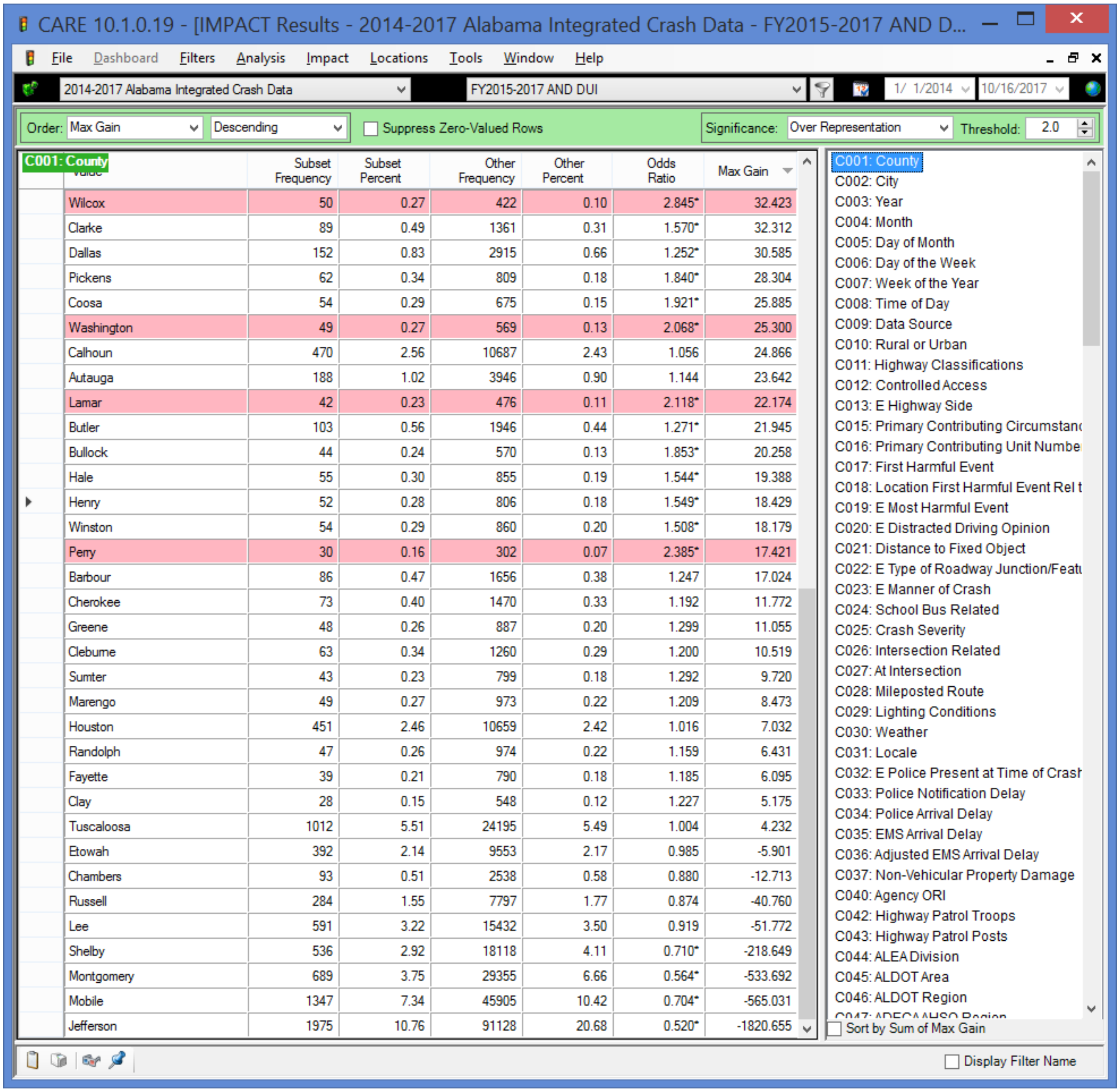
Geographical Factors

County



C001: County Value	Subset Frequency	Subset Percent	Other Frequency	Other Percent	Odds Ratio	Max Gain
Cullman	524	2.86	6718	1.52	1.873*	244.182
Madison	1608	8.76	33446	7.59	1.154*	214.910
Baldwin	847	4.62	15209	3.45	1.337*	213.516
Marshall	441	2.40	7157	1.62	1.479*	142.897
Blount	239	1.30	2472	0.56	2.321*	136.036
Talladega	337	1.84	5333	1.21	1.517*	114.870
Jackson	233	1.27	2962	0.67	1.889*	109.627
St Clair	342	1.86	5686	1.29	1.444*	105.167
Elmore	330	1.80	5572	1.26	1.422*	97.916
Lauderdale	373	2.03	6611	1.50	1.355*	97.639
Limestone	288	1.57	4689	1.06	1.475*	92.694
Chilton	207	1.13	2884	0.65	1.723*	86.876
Dekalb	231	1.26	3554	0.81	1.560*	82.969
Walker	274	1.49	4630	1.05	1.421*	81.152
Escambia	166	0.90	2337	0.53	1.705*	68.659
Tallapoosa	145	0.79	1956	0.44	1.780*	63.529
Geneva	113	0.62	1191	0.27	2.278*	63.393
Dale	168	0.92	2593	0.59	1.556*	59.997
Pike	191	1.04	3158	0.72	1.452*	59.463
Franklin	122	0.66	1584	0.36	1.849*	56.023
Lowndes	93	0.51	914	0.21	2.443*	54.930
Morgan	439	2.39	9221	2.09	1.143*	54.928
Covington	133	0.72	1886	0.43	1.693*	54.444
Macon	135	0.74	1970	0.45	1.645*	52.946
Colbert	256	1.40	4935	1.12	1.245*	50.448
Lawrence	109	0.59	1443	0.33	1.814*	48.896
Coffee	192	1.05	3514	0.80	1.312*	45.635
Monroe	83	0.45	931	0.21	2.140*	44.222
Conecuh	88	0.48	1073	0.24	1.969*	43.307
Choctaw	61	0.33	500	0.11	2.929*	40.174
Crenshaw	69	0.38	729	0.17	2.272*	38.636
Bibb	76	0.41	970	0.22	1.881*	35.598
Marion	97	0.53	1492	0.34	1.561*	34.855
Wilcox	50	0.27	422	0.10	2.845*	32.423

The above has been arranged in highest Max Gain order to indicate the counties that have the highest potential for gain (by reducing the over-representation) at the top. The following output is the rest of the counties in the ordering, so it contains those that are under-represented.



C001: County	Subset Frequency	Subset Percent	Other Frequency	Other Percent	Odds Ratio	Max Gain
Wilcox	50	0.27	422	0.10	2.845*	32.423
Clarke	89	0.49	1361	0.31	1.570*	32.312
Dallas	152	0.83	2915	0.66	1.252*	30.585
Pickens	62	0.34	809	0.18	1.840*	28.304
Coosa	54	0.29	675	0.15	1.921*	25.885
Washington	49	0.27	569	0.13	2.068*	25.300
Calhoun	470	2.56	10687	2.43	1.056	24.866
Autauga	188	1.02	3946	0.90	1.144	23.642
Lamar	42	0.23	476	0.11	2.118*	22.174
Butler	103	0.56	1946	0.44	1.271*	21.945
Bullock	44	0.24	570	0.13	1.853*	20.258
Hale	55	0.30	855	0.19	1.544*	19.388
Henry	52	0.28	806	0.18	1.549*	18.429
Winston	54	0.29	860	0.20	1.508*	18.179
Perry	30	0.16	302	0.07	2.385*	17.421
Barbour	86	0.47	1656	0.38	1.247	17.024
Cherokee	73	0.40	1470	0.33	1.192	11.772
Greene	48	0.26	887	0.20	1.299	11.055
Cleburne	63	0.34	1260	0.29	1.200	10.519
Sumter	43	0.23	799	0.18	1.292	9.720
Marengo	49	0.27	973	0.22	1.209	8.473
Houston	451	2.46	10659	2.42	1.016	7.032
Randolph	47	0.26	974	0.22	1.159	6.431
Fayette	39	0.21	790	0.18	1.185	6.095
Clay	28	0.15	548	0.12	1.227	5.175
Tuscaloosa	1012	5.51	24195	5.49	1.004	4.232
Etowah	392	2.14	9553	2.17	0.985	-5.901
Chambers	93	0.51	2538	0.58	0.880	-12.713
Russell	284	1.55	7797	1.77	0.874	-40.760
Lee	591	3.22	15432	3.50	0.919	-51.772
Shelby	536	2.92	18118	4.11	0.710*	-218.649
Montgomery	689	3.75	29355	6.66	0.564*	-533.692
Mobile	1347	7.34	45905	10.42	0.704*	-565.031
Jefferson	1975	10.76	91128	20.68	0.520*	-1820.655

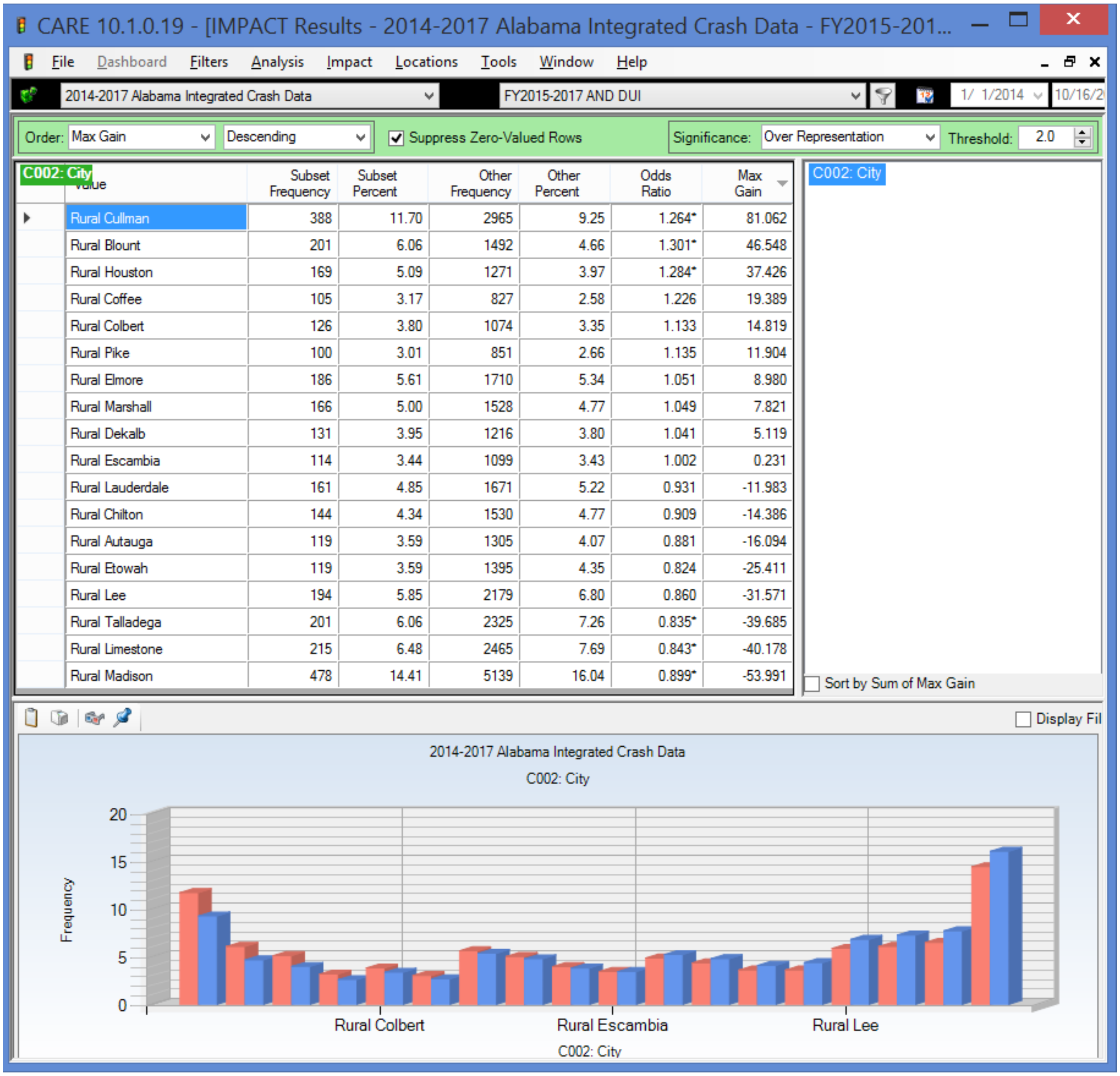
Cullman, Madison, Baldwin, Marshall and Blount have the highest potential for ID crash reduction. At the other end of the spectrum, the counties with the largest cities (e.g., Jefferson, Mobile and Montgomery counties) were the most under-represented counties for impaired driving crashes. Generally, the over-represented counties contain larger rural areas. See the rural-urban comparison below.

Cities Over-represented by Twice the Expected Proportions

For comparison purposes, the rural areas of counties are considered to be "virtual cities" in that crashes that occur there are listed as "Rural County" so that these crashes can be duly accounted for. Generally those rural areas that are adjacent to (or contain) significant urban areas. Contrasted with this finding, there was significant under-representation for impaired driving crashes in the largest cities themselves (e.g., Birmingham, Mobile, Montgomery, Huntsville, Tuscaloosa, etc.). This can be attributed to a number of possible factors in urban areas:

- Less need for motor vehicle travel to the drinking establishments;
- Larger police presence in the metropolitan areas; and
- Lower speeds in rural areas result in a lower severity of crashes, which may be less apt to be reported as caused by impaired driving. Urban crashes contain many described as fender-benders or low-speed rear-end bumper crashes.

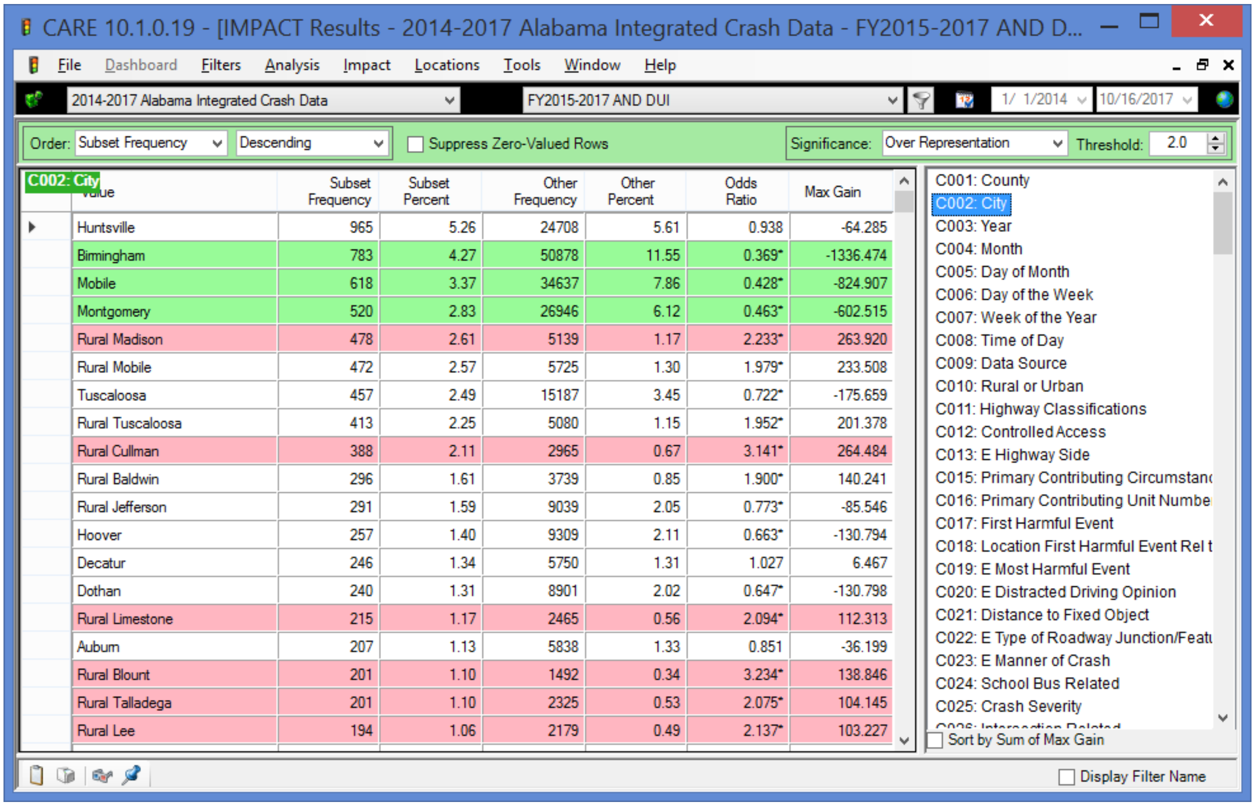
The output display below is a list of what are considered to be the most critical cities because of their proportional increases in FY2017 over that occurring in FY2015-2016. The criteria for this list was (1) a total of 100 or more ID crashes in FY2015-2017, and (2) at least twice the expected proportion in the original state-wide IMPACT run. Note that the reduced IMPACT run displayed is a comparison of only the cities shown, so the Odds Ratios do not show the original over-representations, all of which were over 2.00. This display has been placed in Max Gain ordering to put those cities that have the highest potential for ID crash reduction at the top; however, since the original comparison showed all of these (virtual) cities to have an Odds Ratio of greater than 2.00, they should all be of comparable potential for reduction.



C002: City Value	Subset Frequency	Subset Percent	Other Frequency	Other Percent	Odds Ratio	Max Gain
Rural Cullman	388	11.70	2965	9.25	1.264*	81.062
Rural Blount	201	6.06	1492	4.66	1.301*	46.548
Rural Houston	169	5.09	1271	3.97	1.284*	37.426
Rural Coffee	105	3.17	827	2.58	1.226	19.389
Rural Colbert	126	3.80	1074	3.35	1.133	14.819
Rural Pike	100	3.01	851	2.66	1.135	11.904
Rural Elmore	186	5.61	1710	5.34	1.051	8.980
Rural Marshall	166	5.00	1528	4.77	1.049	7.821
Rural Dekalb	131	3.95	1216	3.80	1.041	5.119
Rural Escambia	114	3.44	1099	3.43	1.002	0.231
Rural Lauderdale	161	4.85	1671	5.22	0.931	-11.983
Rural Chilton	144	4.34	1530	4.77	0.909	-14.386
Rural Autauga	119	3.59	1305	4.07	0.881	-16.094
Rural Etowah	119	3.59	1395	4.35	0.824	-25.411
Rural Lee	194	5.85	2179	6.80	0.860	-31.571
Rural Talladega	201	6.06	2325	7.26	0.835*	-39.685
Rural Limestone	215	6.48	2465	7.69	0.843*	-40.178
Rural Madison	478	14.41	5139	16.04	0.899*	-53.991

Cities by Number of ID Crashes in FY2015-2017

The following display gives the cities with over 200 ID crashes in FY2015-2017

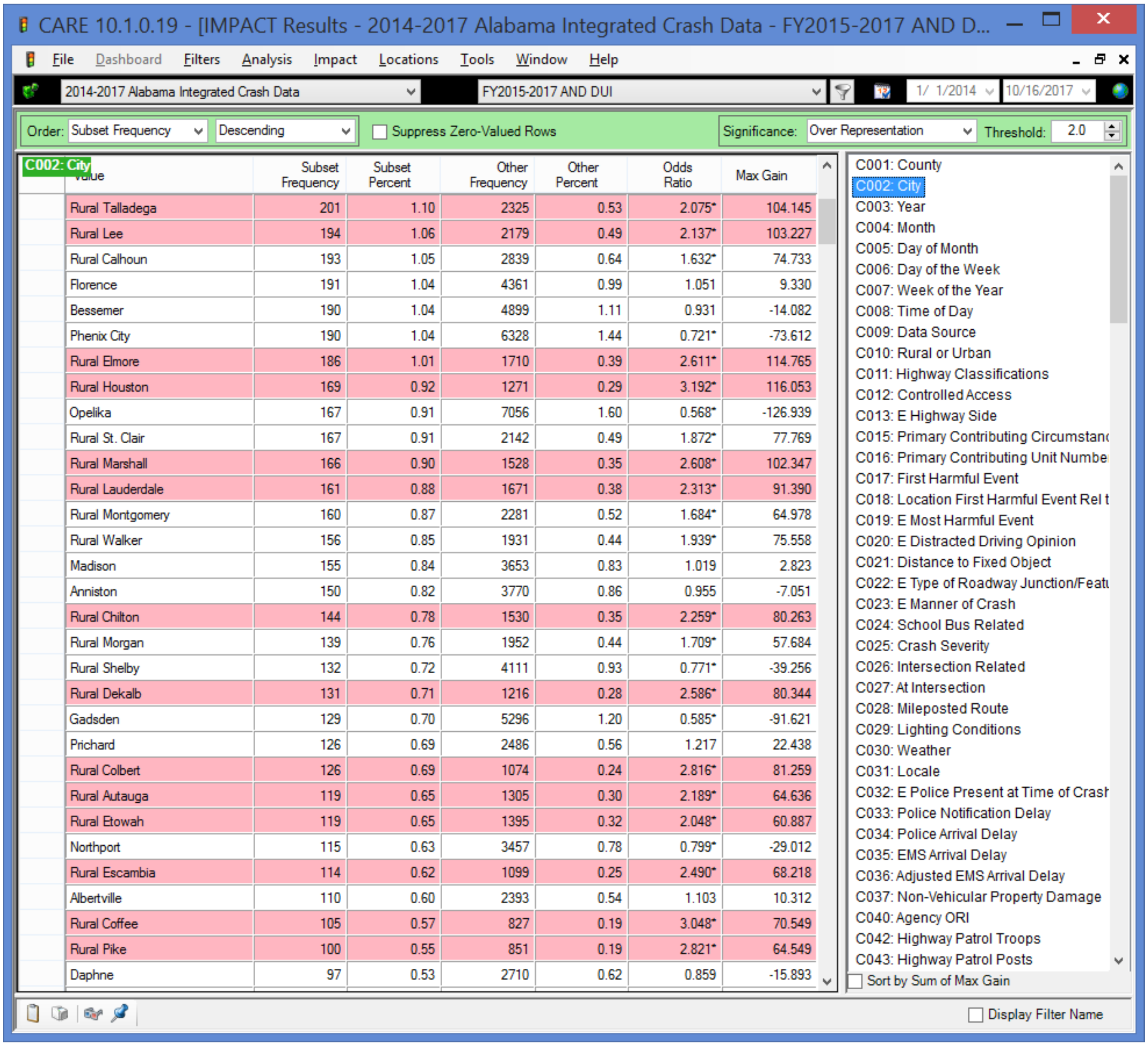


Value	Subset Frequency	Subset Percent	Other Frequency	Other Percent	Odds Ratio	Max Gain
Huntsville	965	5.26	24708	5.61	0.938	-64.285
Birmingham	783	4.27	50878	11.55	0.369*	-1336.474
Mobile	618	3.37	34637	7.86	0.428*	-824.907
Montgomery	520	2.83	26946	6.12	0.463*	-602.515
Rural Madison	478	2.61	5139	1.17	2.233*	263.920
Rural Mobile	472	2.57	5725	1.30	1.979*	233.508
Tuscaloosa	457	2.49	15187	3.45	0.722*	-175.659
Rural Tuscaloosa	413	2.25	5080	1.15	1.952*	201.378
Rural Cullman	388	2.11	2965	0.67	3.141*	264.484
Rural Baldwin	296	1.61	3739	0.85	1.900*	140.241
Rural Jefferson	291	1.59	9039	2.05	0.773*	-85.546
Hoover	257	1.40	9309	2.11	0.663*	-130.794
Decatur	246	1.34	5750	1.31	1.027	6.467
Dothan	240	1.31	8901	2.02	0.647*	-130.798
Rural Limestone	215	1.17	2465	0.56	2.094*	112.313
Auburn	207	1.13	5838	1.33	0.851	-36.199
Rural Blount	201	1.10	1492	0.34	3.234*	138.846
Rural Talladega	201	1.10	2325	0.53	2.075*	104.145
Rural Lee	194	1.06	2179	0.49	2.137*	103.227

Huntsville, at the top of the list, is interesting in that it also has a relatively high proportion of non-ID crashes (5.61%). And while it is at the top of the list for frequency, it is slightly under-represented in ID crashes (5.26/5.61=0.938). The three largest cities that follow are shown with a green background in that their Odds Ratios are less than 0.500, i.e., they have less than half of the ID crashes that you would expect from the proportion of non-ID crashes.

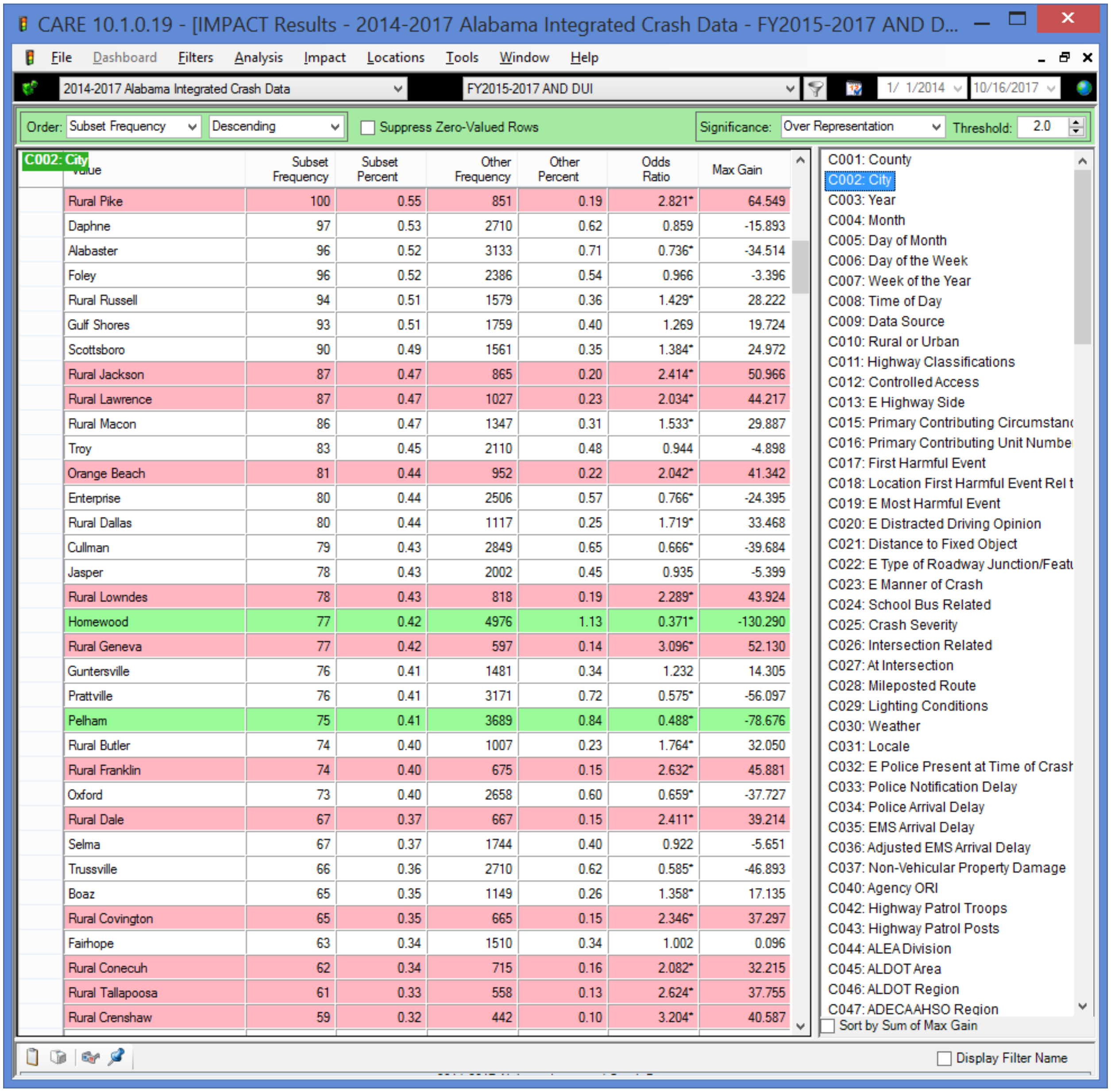
Use the Odds Ratio to determine which of these cities has more ID crashes (labeled Subset) than would be expected based on their non-ID crashes (labeled Other). The red background indicates that the cell has over twice the expected number of ID crashes.

The following lists cities with 100-200 ID crashes, where some overlap with the other tables is shown in the first and last cells.



Value	Subset Frequency	Subset Percent	Other Frequency	Other Percent	Odds Ratio	Max Gain
Rural Talladega	201	1.10	2325	0.53	2.075*	104.145
Rural Lee	194	1.06	2179	0.49	2.137*	103.227
Rural Calhoun	193	1.05	2839	0.64	1.632*	74.733
Florence	191	1.04	4361	0.99	1.051	9.330
Bessemer	190	1.04	4899	1.11	0.931	-14.082
Phenix City	190	1.04	6328	1.44	0.721*	-73.612
Rural Elmore	186	1.01	1710	0.39	2.611*	114.765
Rural Houston	169	0.92	1271	0.29	3.192*	116.053
Opelika	167	0.91	7056	1.60	0.568*	-126.939
Rural St. Clair	167	0.91	2142	0.49	1.872*	77.769
Rural Marshall	166	0.90	1528	0.35	2.608*	102.347
Rural Lauderdale	161	0.88	1671	0.38	2.313*	91.390
Rural Montgomery	160	0.87	2281	0.52	1.684*	64.978
Rural Walker	156	0.85	1931	0.44	1.939*	75.558
Madison	155	0.84	3653	0.83	1.019	2.823
Anniston	150	0.82	3770	0.86	0.955	-7.051
Rural Chilton	144	0.78	1530	0.35	2.259*	80.263
Rural Morgan	139	0.76	1952	0.44	1.709*	57.684
Rural Shelby	132	0.72	4111	0.93	0.771*	-39.256
Rural Dekalb	131	0.71	1216	0.28	2.586*	80.344
Gadsden	129	0.70	5296	1.20	0.585*	-91.621
Prichard	126	0.69	2486	0.56	1.217	22.438
Rural Colbert	126	0.69	1074	0.24	2.816*	81.259
Rural Autauga	119	0.65	1305	0.30	2.189*	64.636
Rural Etowah	119	0.65	1395	0.32	2.048*	60.887
Northport	115	0.63	3457	0.78	0.799*	-29.012
Rural Escambia	114	0.62	1099	0.25	2.490*	68.218
Albertville	110	0.60	2393	0.54	1.103	10.312
Rural Coffee	105	0.57	827	0.19	3.048*	70.549
Rural Pike	100	0.55	851	0.19	2.821*	64.549
Daphne	97	0.53	2710	0.62	0.859	-15.893

The following lists cities with 60-100 ID crashes, where some overlap with the other tables is shown in the first and last cells.



Value	Subset Frequency	Subset Percent	Other Frequency	Other Percent	Odds Ratio	Max Gain
Rural Pike	100	0.55	851	0.19	2.821*	64.549
Daphne	97	0.53	2710	0.62	0.859	-15.893
Alabaster	96	0.52	3133	0.71	0.736*	-34.514
Foley	96	0.52	2386	0.54	0.966	-3.396
Rural Russell	94	0.51	1579	0.36	1.429*	28.222
Gulf Shores	93	0.51	1759	0.40	1.269	19.724
Scottsboro	90	0.49	1561	0.35	1.384*	24.972
Rural Jackson	87	0.47	865	0.20	2.414*	50.966
Rural Lawrence	87	0.47	1027	0.23	2.034*	44.217
Rural Macon	86	0.47	1347	0.31	1.533*	29.887
Troy	83	0.45	2110	0.48	0.944	-4.898
Orange Beach	81	0.44	952	0.22	2.042*	41.342
Enterprise	80	0.44	2506	0.57	0.766*	-24.395
Rural Dallas	80	0.44	1117	0.25	1.719*	33.468
Cullman	79	0.43	2849	0.65	0.666*	-39.684
Jasper	78	0.43	2002	0.45	0.935	-5.399
Rural Lowndes	78	0.43	818	0.19	2.289*	43.924
Homewood	77	0.42	4976	1.13	0.371*	-130.290
Rural Geneva	77	0.42	597	0.14	3.096*	52.130
Guntersville	76	0.41	1481	0.34	1.232	14.305
Prattville	76	0.41	3171	0.72	0.575*	-56.097
Pelham	75	0.41	3689	0.84	0.488*	-78.676
Rural Butler	74	0.40	1007	0.23	1.764*	32.050
Rural Franklin	74	0.40	675	0.15	2.632*	45.881
Oxford	73	0.40	2658	0.60	0.659*	-37.727
Rural Dale	67	0.37	667	0.15	2.411*	39.214
Selma	67	0.37	1744	0.40	0.922	-5.651
Trussville	66	0.36	2710	0.62	0.585*	-46.893
Boaz	65	0.35	1149	0.26	1.358*	17.135
Rural Covington	65	0.35	665	0.15	2.346*	37.297
Fairhope	63	0.34	1510	0.34	1.002	0.096
Rural Conecuh	62	0.34	715	0.16	2.082*	32.215
Rural Tallapoosa	61	0.33	558	0.13	2.624*	37.755
Rural Crenshaw	59	0.32	442	0.10	3.204*	40.587

Severity of Crash by Rural-Urban

It is obvious in the above outputs that the rural areas tend to be more over-represented in ID crashes than do the urbanized areas. It is interesting to perform a cross-tabulation over the rural and urban areas to determine to what extent their crashes might be causing relatively more fatalities than would be expected from just a comparison of their crash frequencies. The following gives this analysis.

CARE 10.1.0.19 - [Crosstab Results - 2014-2017 Alabama Integrated Crash Data - Filte...

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2014-2017 Alabama Integrated Crash Data | FY2015-2017 AND DUI | 1/ 1/2014

Suppress Zero Values: None | Select Cells: | Column: Crash Severity ; Row: Rural or Urban

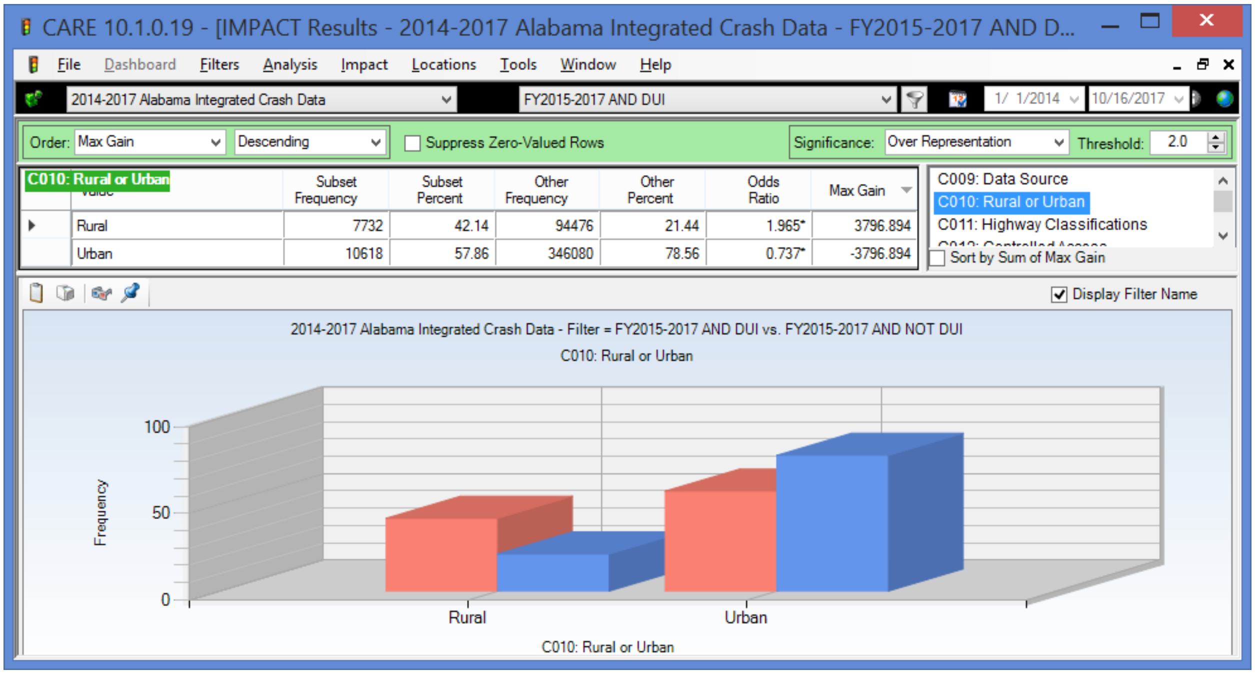
	Fatal Injury	Incapacitating Injury	Non-Incapacitating Inju	Possible Injury	Property Damage Only	Unknown	TOTAL
Rural	415 66.94%	1330 61.38%	1512 49.19%	429 25.58%	3969 38.31%	77 17.04%	7732 42.14%
Urban	205 33.06%	837 38.62%	1562 50.81%	1248 74.42%	6391 61.69%	375 82.96%	10618 57.86%
TOTAL	620 3.38%	2167 11.81%	3074 16.75%	1677 9.14%	10360 56.46%	452 2.46%	18350 100.00%

The red cells in the cross-tabulation above indicate over-representation by more than 10%. For example, while 42.14% of crashes occur in rural areas, close to 67% of the fatal crashes occur there. It is imperative to take into consideration crash severity when making geographical decisions regarding countermeasure implementation. Any of the geographic analyses shown in this report could be restricted to fatal crashes or some combination of fatal and injury crashes.

Clearly fatalities and the highest severity of injuries are over-represented in the rural areas.

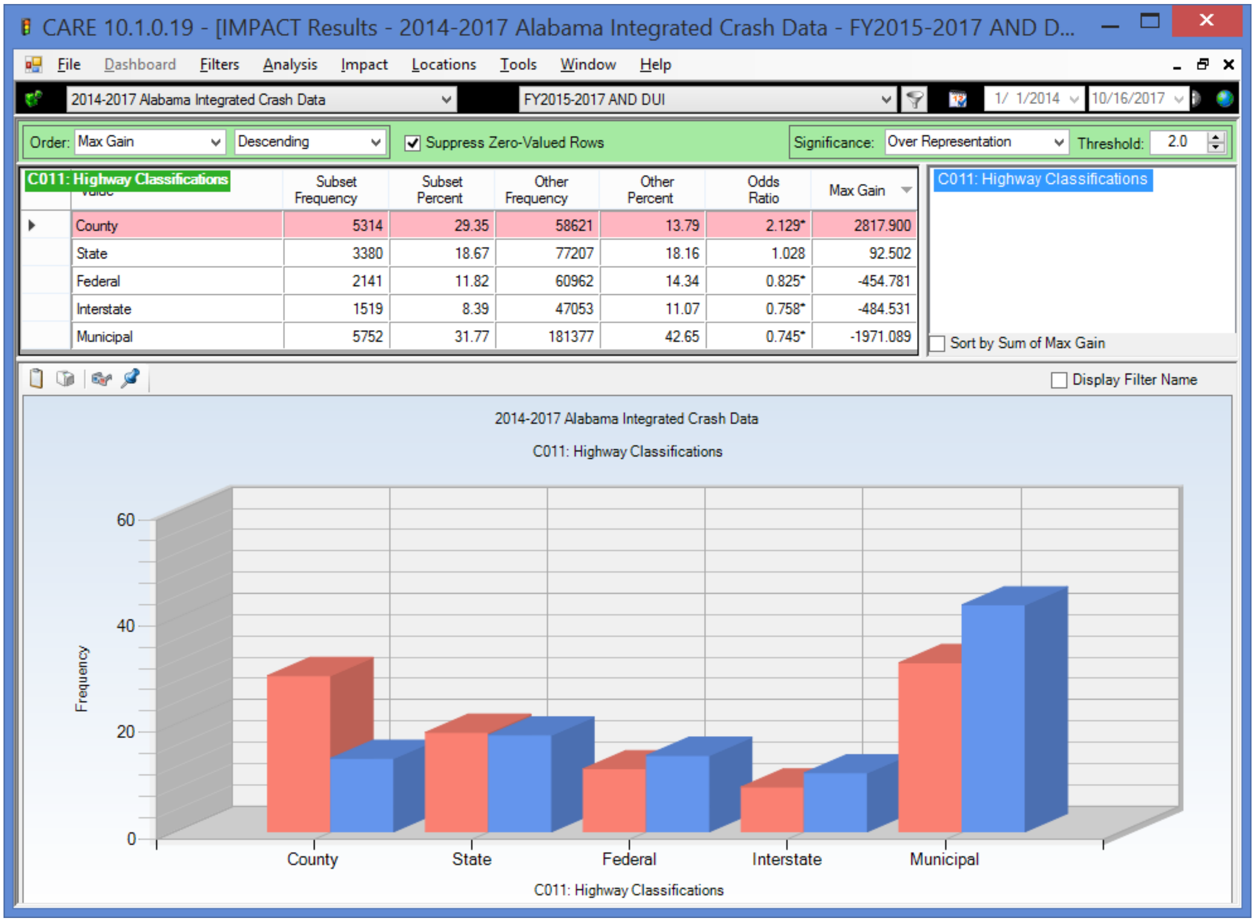
Some recent ads have stated that the urban areas contain the ID hotspots. This is only true if looking at the total frequency of the ID crashes as the criterion and ignoring severity. It also ignores the high number of crashes in general that are expected to occur in population centers.

Rural or Urban



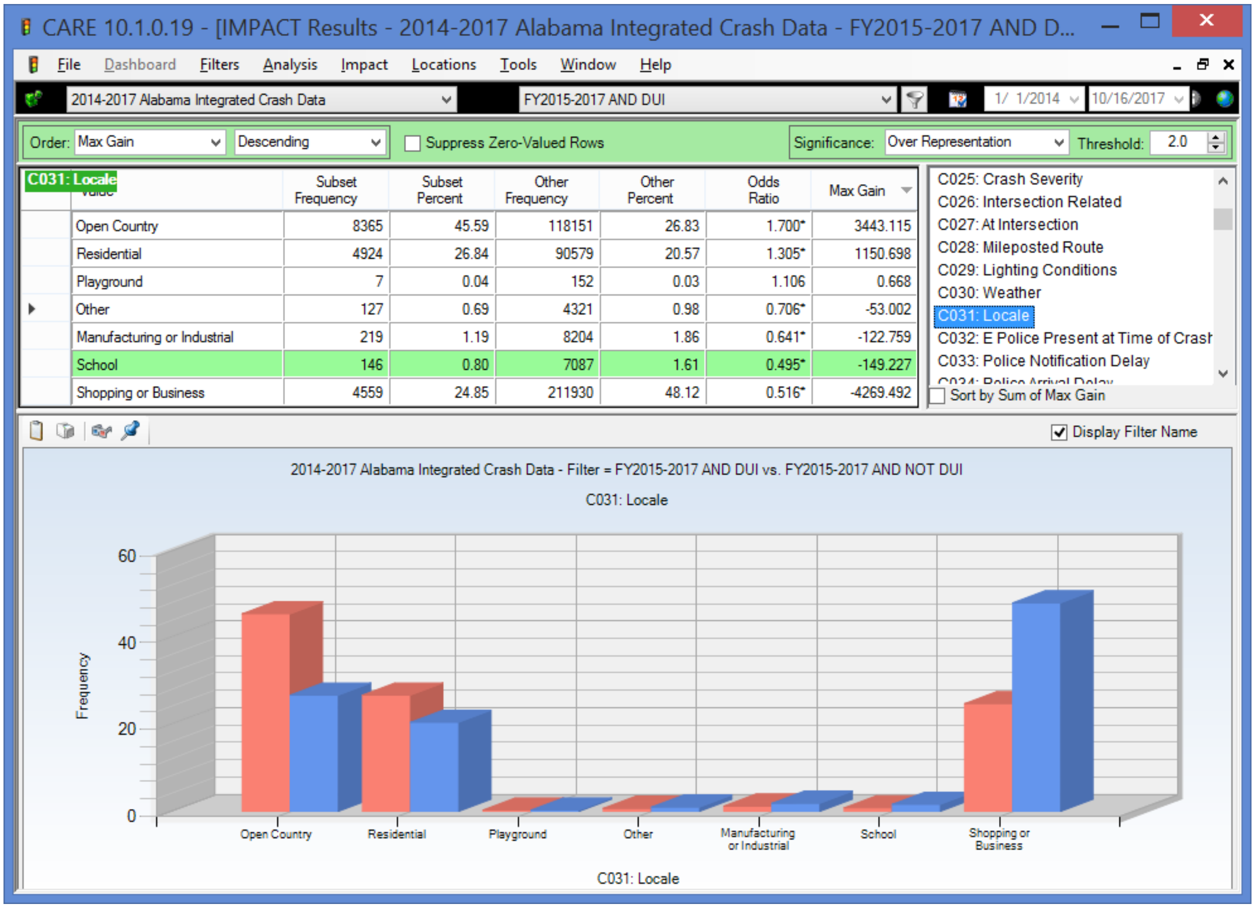
Not only are impaired driving crashes more severe in rural areas, but the chart above shows that 42.14% of the ID crashes occur in the rural areas. This is about double what would be expected from the rural crashes in general (21.44%).

Highway Classifications



Analysis of highway classifications indicates that ID crashes had their greatest over-representation on county roads. County roads had well over twice their expected proportion of crashes, while all other roadway classifications were under-represented. It is very possible that ID locals in the rural areas use the county road system to evade police. Their cunning in this regard does not seem to extend to making it home safely. It is recommended that further analysis be performed to identify the specific county roads that are most highly over-represented, and that some enforcement activities be conducted on the county roads in an attempt to move the ID traffic onto the safer (more forgiving) roadways.

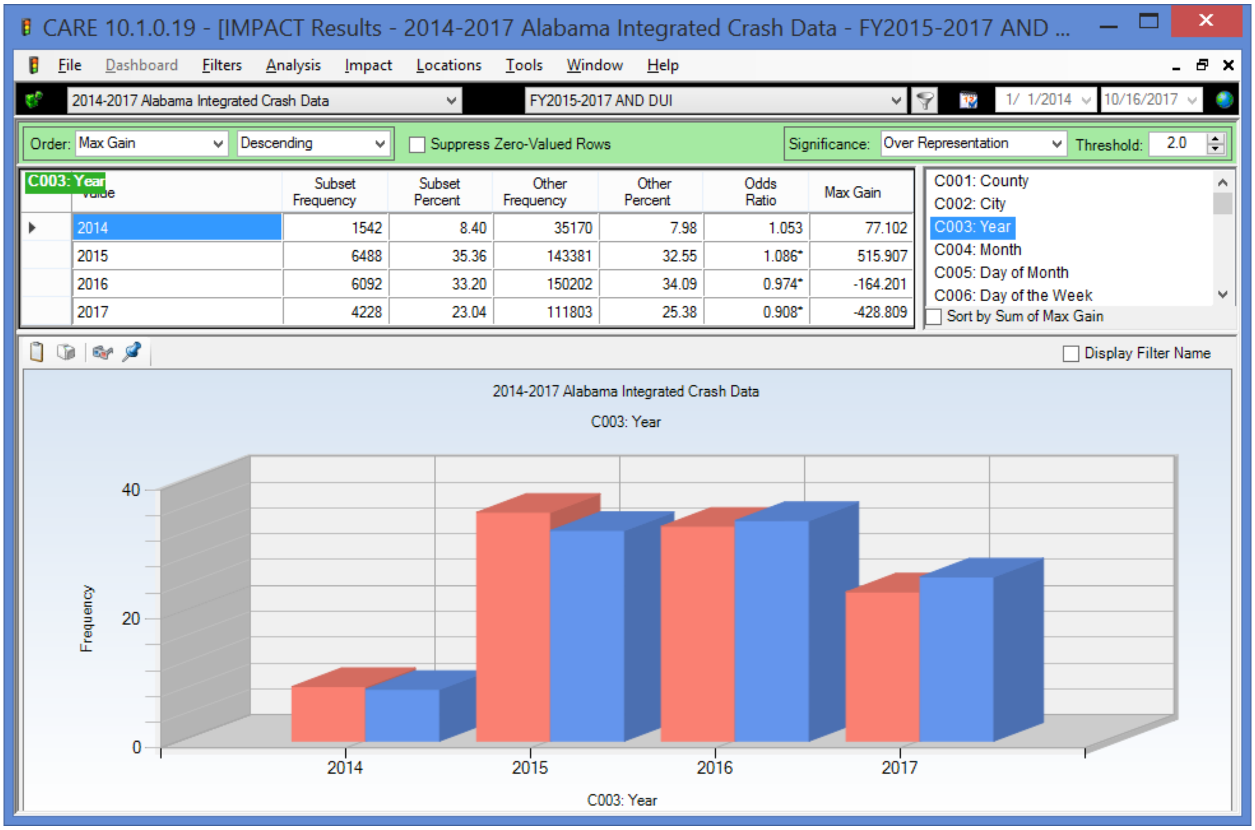
Locale



Reflecting the urban over-representation, open country and residential roadways show a higher level of over-representation as compared to the more urbanized roadways.

Time Factors

Year

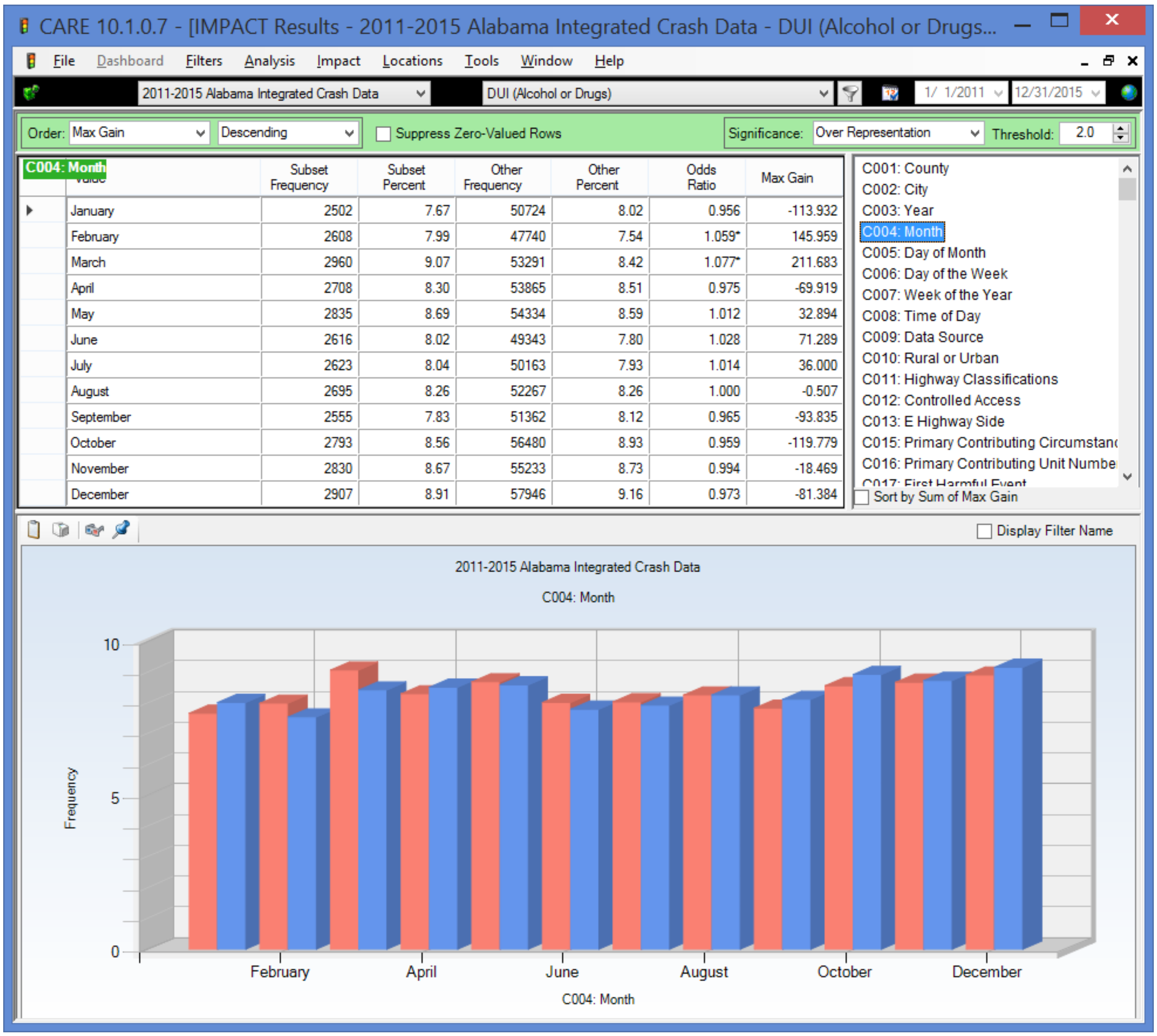


See the Introduction section for a crash frequency comparison of the three fiscal years being considered in these analyses. While the above cannot give a good reading on the overall absolute increase/decrease in ID crashes, it is useful for tracking the relative changes. This is because the 2014 calendar year is only three months (October-December), while the 2017 calendar year displayed is only 9 months (January-September).

However, this does not prevent us from discovering that ID crashes were significantly over-represented in CY2015. The two were almost as expected in the last three months of 2014. In CY2015 the proportion of ID crashes was significantly higher than that for non-ID crashes. This trend was reversed for CY 2016 where almost the opposite under-representation occurred. This gain continued into the first nine months of 2017, and a benefit of nearly 429 crashes was obtained for ID in comparison to the non-ID crash proportion.

This is a good time to emphasize that the ID reports being considered here are those reported to have been DUI (Alcohol or Drugs), which is about 6% of the total reported crashes. While this is an accurate statement of the number reported as such, no one claims that this is the actual number of ID crashes. Many ID caused crashes cannot be verified, and they are therefore not reported as such. These reports over time provide excellent insight into the nature of ID crashes despite their not being a complete set of ID reports. As the severity of the crashes increases, the completeness of the reports in attributing them to ID also increased dramatically. For example, the amount of effort that goes into investigating a fatal crash is at least 10 to 20 times more effort than goes into reporting and obtaining all of the details of most property damage only crashes.

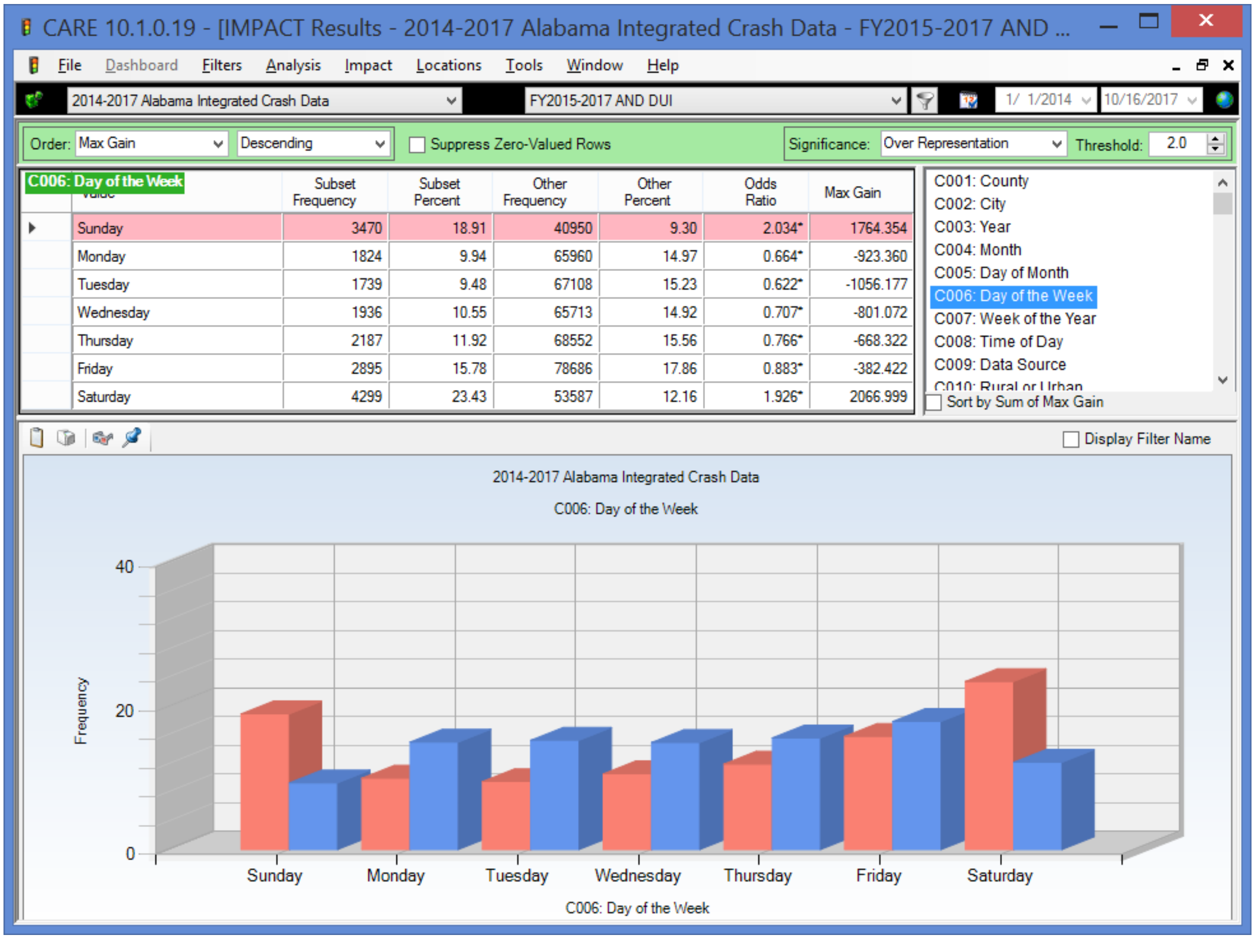
Month



C004: Month	Subset Frequency	Subset Percent	Other Frequency	Other Percent	Odds Ratio	Max Gain
January	2502	7.67	50724	8.02	0.956	-113.932
February	2608	7.99	47740	7.54	1.059*	145.959
March	2960	9.07	53291	8.42	1.077*	211.683
April	2708	8.30	53865	8.51	0.975	-69.919
May	2835	8.69	54334	8.59	1.012	32.894
June	2616	8.02	49343	7.80	1.028	71.289
July	2623	8.04	50163	7.93	1.014	36.000
August	2695	8.26	52267	8.26	1.000	-0.507
September	2555	7.83	51362	8.12	0.965	-93.835
October	2793	8.56	56480	8.93	0.959	-119.779
November	2830	8.67	55233	8.73	0.994	-18.469
December	2907	8.91	57946	9.16	0.973	-81.384

The only significant over-representations by month were in February and March, and there we no significant under-representations. Otherwise the number of ID crashes correlated well with non-ID crashes during each of the remaining months.

Day of the Week



C006: Day of the Week Value	Subset Frequency	Subset Percent	Other Frequency	Other Percent	Odds Ratio	Max Gain
Sunday	3470	18.91	40950	9.30	2.034*	1764.354
Monday	1824	9.94	65960	14.97	0.664*	-923.360
Tuesday	1739	9.48	67108	15.23	0.622*	-1056.177
Wednesday	1936	10.55	65713	14.92	0.707*	-801.072
Thursday	2187	11.92	68552	15.56	0.766*	-668.322
Friday	2895	15.78	78686	17.86	0.883*	-382.422
Saturday	4299	23.43	53587	12.16	1.926*	2066.999

The chart above shows the typical non-holiday week pattern that has been experienced for ID for decades. The days can be classified as follows:

- Weekday (Monday through Thursday) – these days are under-represented in ID crashes we would surmise due to the need for many to go to work the following day.
- Friday – the day before a weekend (or holiday) before a day off work. The Friday pattern is slightly under-represented in ID crashes, not because they do not occur more frequently than weekdays, but because non-ID crashes occur even more. This is due to the in-creased traffic of combined commuters and vacationers (including short week-end vaca-tions) that causes a bad traffic mix. It may be only slightly denser than a typical rush hour, but it is not homogeneous and restricted to commuters as is the case during most

weekday rush hours. No doubt much drug use and increased alcohol consumption is initiated on Friday afternoons.

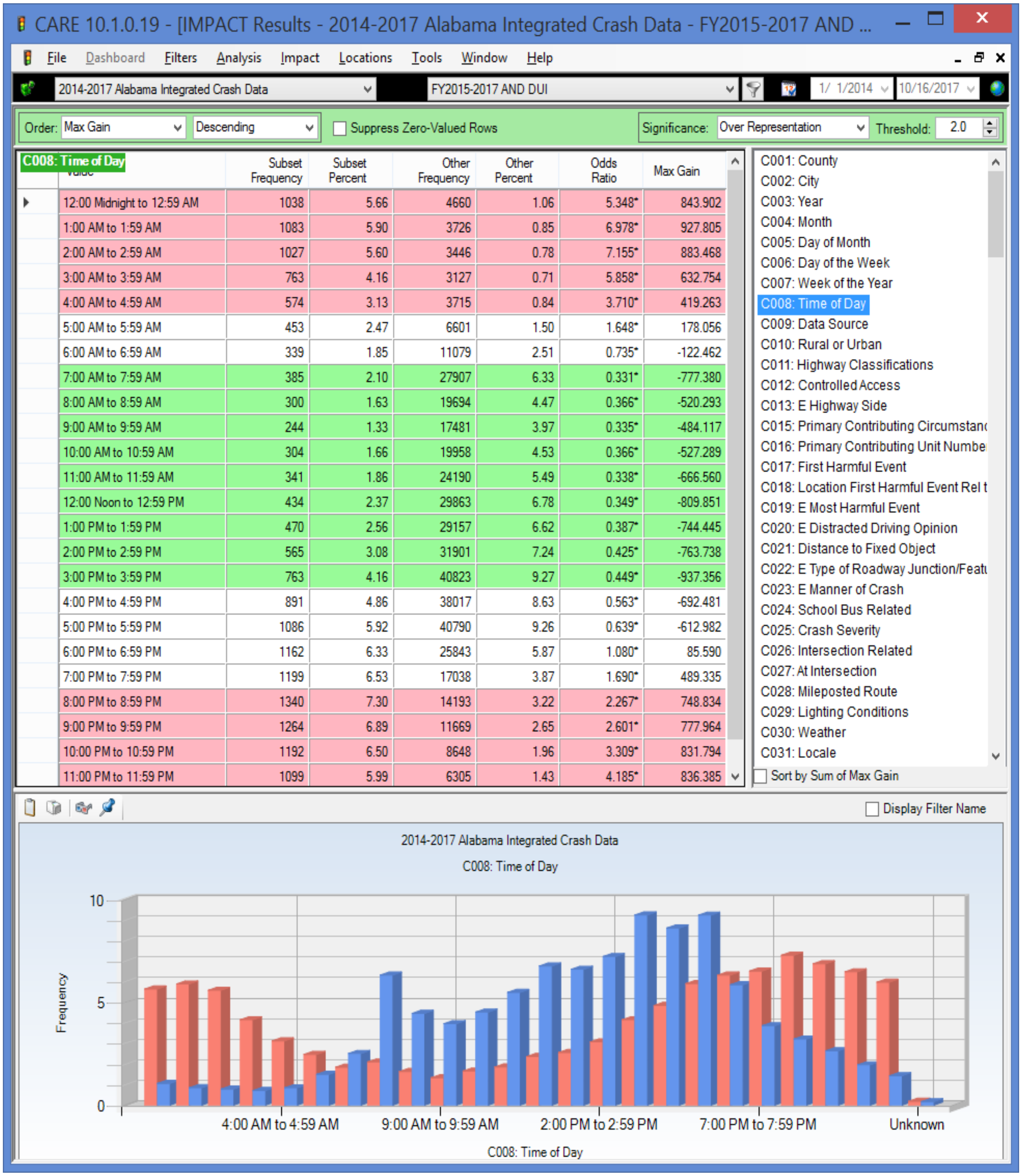
- Saturday – the "Saturday" pattern is the worse for ID crashes in that it has both an early morning component (like Sunday) and a late (pre-midnight) night component (like Friday). So, it could be viewed as a combination of the typical Friday and Sunday, with one exception. It does not have the increased complexity of the Friday afternoon commuters.
- Sunday – this is the last day of a holiday sequence or as given above, the weekend. Its over-representation comes strictly from those who start on Saturday night and do not complete their use of alcohol/drugs until after midnight.

A holiday "weekend," such as Thanksgiving, can be viewed as a sequence of a Friday-, Saturdays- and Sunday-pattern sequence. The Wednesday before Thanksgiving would follow the Friday pattern assuming that most are at work that Wednesday. The Thursday, Friday and Saturday would follow the Saturday pattern, and the Sunday would follow the typical Sunday pattern. Holidays that fall mid-week could also be so mapped. This is the reason that long holiday events (i.e., several days off from work) can be much more prone to ID crashes than the normal weekend. There could be a cumulative effect that could show up at any time of the day for some problem abusers. Recently the trend on the pre-Thanksgiving week has been for the holiday to start earlier and earlier in the week, so that Wednesday itself is not one of the worse crash days of the year, as it had been a decade or more ago. This if favorable in reducing the concentration of the traffic and the resultant conflicts.

Time of Day

It is no surprise to find ID crashes over-represented during the late night/early morning hours. The extent of these over-representations, however, is quite amazing. The blue bars above follow the typical traffic patterns of high traffic in the morning and afternoon rush hours. ID crashes are just getting started in the afternoon rush hours and they continue to grow through midnight and the early morning hours, not tapering off until about 5:00 AM. It is clear that if selective enforcement is going to have an effect on ID crashes, it would have to be conducted at the times when these crashes are most occurring. Optimal times for enforcement would start immediately following any rush hour details, and would continue through at least 3:00 AM.

So generally, the worst times in any day are given in red for that day. This works well for Saturday and Sunday mornings, and also for Friday night. Why does it not work for Saturday night? The answer is that Saturday morning has drained all the red into its cells, so to speak, and there is none left over for Saturday night. Note, for example, that the frequencies of crashes on Saturday exceed those on Friday for *all time slots*. However, because of the high numbers and proportions on Saturday morning, the proportions on Saturday night are lower despite the frequencies being higher. We urge users to look at both the numbers and the colors. This is also especially true when the numbers in all of the cells is relatively low. When the cell numbers get less than 20, it is best to ignore the colors and just look at the cell frequencies to get a feel for the situation.



C008: Time of Day Value	Subset Frequency	Subset Percent	Other Frequency	Other Percent	Odds Ratio	Max Gain
12:00 Midnight to 12:59 AM	1038	5.66	4660	1.06	5.348*	843.902
1:00 AM to 1:59 AM	1083	5.90	3726	0.85	6.978*	927.805
2:00 AM to 2:59 AM	1027	5.60	3446	0.78	7.155*	883.468
3:00 AM to 3:59 AM	763	4.16	3127	0.71	5.858*	632.754
4:00 AM to 4:59 AM	574	3.13	3715	0.84	3.710*	419.263
5:00 AM to 5:59 AM	453	2.47	6601	1.50	1.648*	178.056
6:00 AM to 6:59 AM	339	1.85	11079	2.51	0.735*	-122.462
7:00 AM to 7:59 AM	385	2.10	27907	6.33	0.331*	-777.380
8:00 AM to 8:59 AM	300	1.63	19694	4.47	0.366*	-520.293
9:00 AM to 9:59 AM	244	1.33	17481	3.97	0.335*	-484.117
10:00 AM to 10:59 AM	304	1.66	19958	4.53	0.366*	-527.289
11:00 AM to 11:59 AM	341	1.86	24190	5.49	0.338*	-666.560
12:00 Noon to 12:59 PM	434	2.37	29863	6.78	0.349*	-809.851
1:00 PM to 1:59 PM	470	2.56	29157	6.62	0.387*	-744.445
2:00 PM to 2:59 PM	565	3.08	31901	7.24	0.425*	-763.738
3:00 PM to 3:59 PM	763	4.16	40823	9.27	0.449*	-937.356
4:00 PM to 4:59 PM	891	4.86	38017	8.63	0.563*	-692.481
5:00 PM to 5:59 PM	1086	5.92	40790	9.26	0.639*	-612.982
6:00 PM to 6:59 PM	1162	6.33	25843	5.87	1.080*	85.590
7:00 PM to 7:59 PM	1199	6.53	17038	3.87	1.690*	489.335
8:00 PM to 8:59 PM	1340	7.30	14193	3.22	2.267*	748.834
9:00 PM to 9:59 PM	1264	6.89	11669	2.65	2.601*	777.964
10:00 PM to 10:59 PM	1192	6.50	8648	1.96	3.309*	831.794
11:00 PM to 11:59 PM	1099	5.99	6305	1.43	4.185*	836.385

Time of Day by Day of the Week

CARE 10.1.0.7 - [Crosstab Results - 2011-2015 Alabama Integrated Crash Data - Filter = DUI (Alcohol ...

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2011-2015 Alabama Integrated Crash Data | DUI (Alcohol or Drugs) | 1/ 1/2011 | 12/31/2015

Suppress Zero Values: None | Select Cells: | Column: Day of the Week ; Row: Time of Day

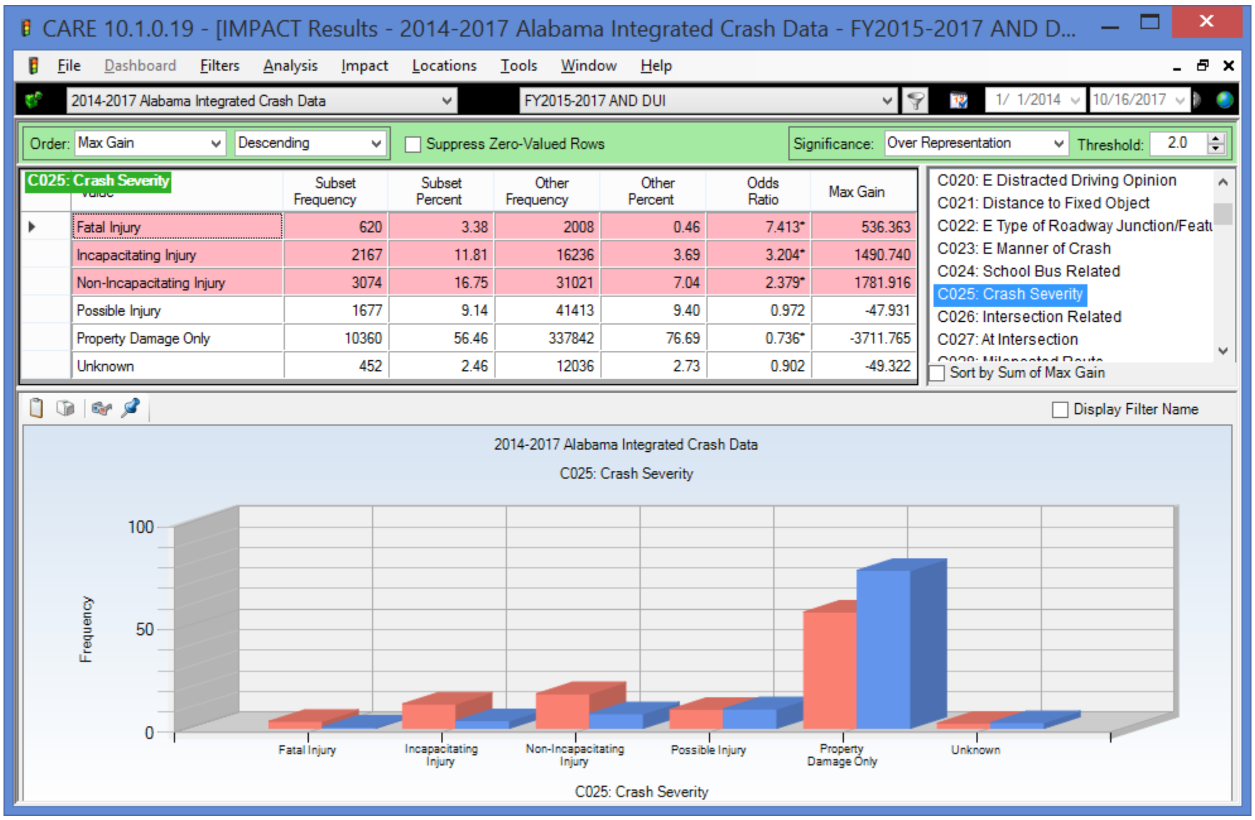
	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	TOTAL
12:00 Midnight to 12:59 AM	544 8.97%	119 3.81%	155 4.79%	175 5.11%	211 5.47%	232 4.48%	472 6.09%	1908 5.85%
1:00 AM to 1:59 AM	602 9.92%	109 3.49%	116 3.59%	137 4.00%	178 4.61%	228 4.40%	583 7.53%	1953 5.98%
2:00 AM to 2:59 AM	629 10.37%	108 3.45%	99 3.06%	125 3.65%	169 4.38%	227 4.39%	570 7.36%	1927 5.91%
3:00 AM to 3:59 AM	465 7.66%	77 2.46%	85 2.63%	75 2.19%	104 2.69%	163 3.15%	504 6.51%	1473 4.51%
4:00 AM to 4:59 AM	342 5.64%	51 1.63%	47 1.45%	62 1.81%	84 2.18%	107 2.07%	377 4.87%	1070 3.28%
5:00 AM to 5:59 AM	289 4.76%	42 1.34%	55 1.70%	49 1.43%	72 1.87%	70 1.35%	240 3.10%	817 2.50%
6:00 AM to 6:59 AM	193 3.18%	54 1.73%	48 1.48%	49 1.43%	73 1.89%	64 1.24%	158 2.04%	639 1.96%
7:00 AM to 7:59 AM	125 2.06%	67 2.14%	90 2.78%	73 2.13%	64 1.66%	79 1.53%	129 1.67%	627 1.92%
8:00 AM to 8:59 AM	73 1.20%	60 1.92%	65 2.01%	68 1.99%	60 1.55%	57 1.10%	96 1.24%	479 1.47%
9:00 AM to 9:59 AM	70 1.15%	56 1.79%	51 1.58%	50 1.46%	49 1.27%	73 1.41%	84 1.08%	433 1.33%
10:00 AM to 10:59 AM	65 1.07%	60 1.92%	59 1.82%	70 2.05%	49 1.27%	94 1.82%	92 1.19%	489 1.50%
11:00 AM to 11:59 AM	84 1.38%	83 2.65%	69 2.13%	74 2.16%	93 2.41%	85 1.64%	118 1.52%	606 1.86%
12:00 Noon to 12:59 PM	91 1.50%	86 2.75%	82 2.54%	96 2.81%	116 3.01%	102 1.97%	134 1.73%	707 2.17%
1:00 PM to 1:59 PM	119 1.96%	93 2.97%	108 3.34%	91 2.66%	97 2.51%	122 2.36%	169 2.18%	799 2.45%
2:00 PM to 2:59 PM	130 2.14%	135 4.32%	131 4.05%	138 4.03%	138 3.58%	167 3.23%	179 2.31%	1018 3.12%
3:00 PM to 3:59 PM	156 2.57%	172 5.50%	178 5.51%	178 5.20%	193 5.00%	213 4.12%	246 3.18%	1336 4.09%
4:00 PM to 4:59 PM	226 3.73%	188 6.01%	199 6.16%	201 5.87%	222 5.75%	261 5.04%	275 3.55%	1572 4.82%
5:00 PM to 5:59 PM	244 4.02%	245 7.83%	245 7.58%	267 7.80%	253 6.55%	310 5.99%	370 4.78%	1934 5.93%
6:00 PM to 6:59 PM	304 5.01%	245 7.83%	242 7.49%	247 7.22%	221 5.73%	312 6.03%	400 5.16%	1971 6.04%
7:00 PM to 7:59 PM	288 4.75%	211 6.75%	210 6.50%	220 6.43%	281 7.28%	336 6.49%	438 5.65%	1984 6.08%
8:00 PM to 8:59 PM	336 5.54%	248 7.93%	272 8.41%	252 7.36%	312 8.08%	390 7.53%	485 6.26%	2295 7.03%
9:00 PM to 9:59 PM	270 4.45%	238 7.61%	236 7.30%	271 7.92%	322 8.34%	486 9.39%	525 6.78%	2348 7.20%
10:00 PM to 10:59 PM	228 3.76%	213 6.81%	220 6.80%	244 7.13%	242 6.27%	459 8.87%	559 7.22%	2165 6.63%
11:00 PM to 11:59 PM	184 3.03%	161 5.15%	167 5.17%	208 6.08%	254 6.58%	532 10.28%	534 6.89%	2040 6.25%
Unknown	10 0.16%	6 0.19%	4 0.12%	2 0.06%	3 0.08%	7 0.14%	10 0.13%	42 0.13%
TOTAL	6067 18.59%	3127 9.58%	3233 9.91%	3422 10.49%	3860 11.83%	5176 15.86%	7747 23.74%	32632 100.00%

The Time of Day by Day of the Week cross-tabulation (given in the next section) shows the optimal times for selective enforcement, with one qualifier: Saturday night (before midnight). This is an excellent example to demonstrate how the color coding of CARE cross-tabulations can be misleading in some special cases. The red background indicates that the over-representation of the cell is greater than expected. The expected proportion for all cells in a given row is given at the extreme right in the total row percentage for that row. If there were absolutely no over-representations for the columns, then all of the proportions for that column cell would be identical to the one for the total. Notice for example, the 12 midnight to 12:59 AM row has a total percentage value of 5.85%. Those that are under this value have a neutral (white) background. Those that are higher, but not more than 10% of the proportion are yellow; and those above 10% of the proportion are red.

Factors Affecting Severity

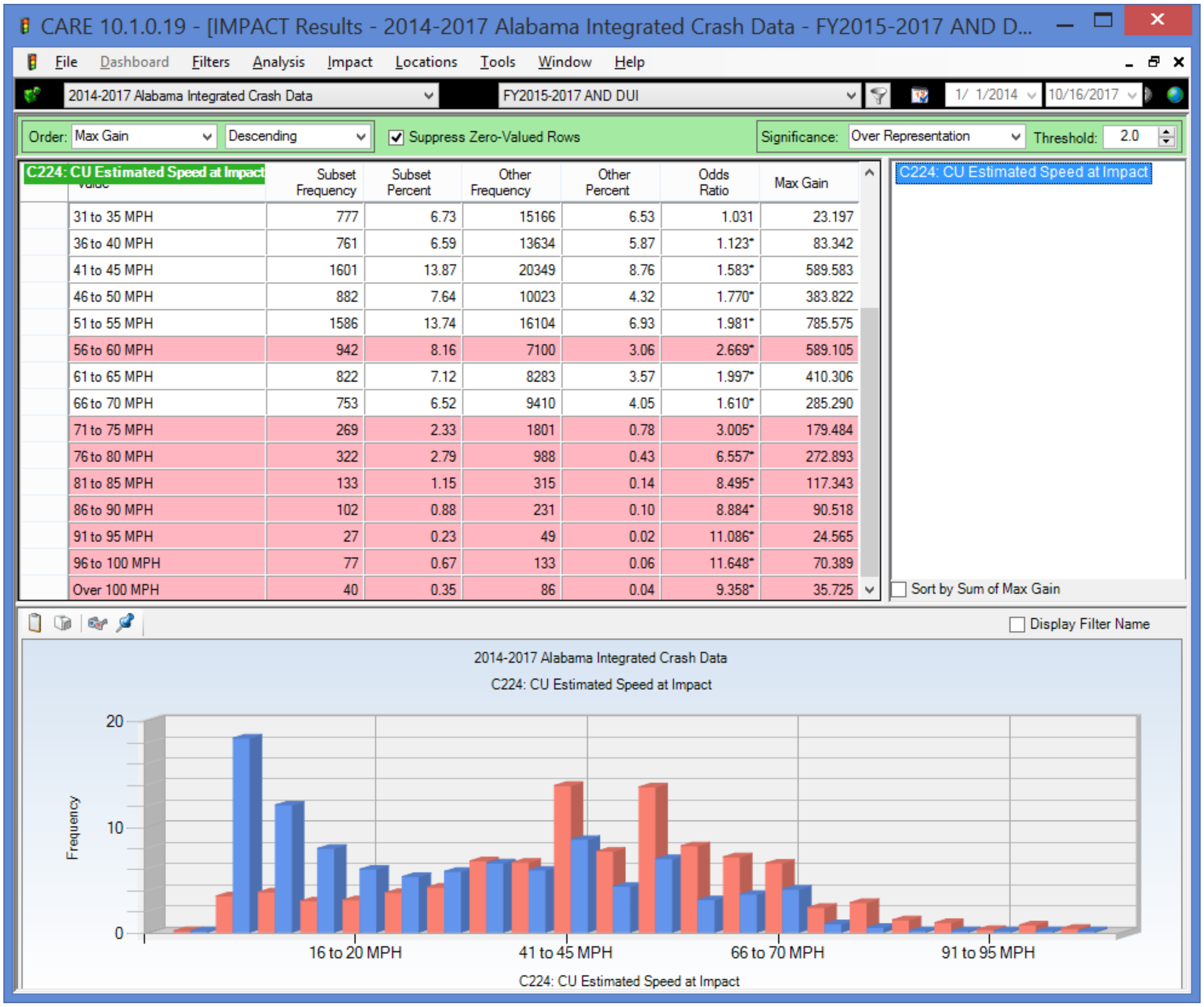
ID Crash Severity

The following compares crash severities for ID (Subset, red bars) vs. Non-ID crashes (Other, blue bars).



The rate of fatal injury crashes and the two highest injury classifications are consistently higher in ID crashes than that of non-ID crashes. Fatality crashes have over seven times their expected proportion, while the two highest non-fatal injury classifications have over twice their expected values when compared with non-impaired driving crashes. The Speed-at-Impact variable, considered next, indicates one of the primary reasons for this.

Speed at Impact



C224: CU Estimated Speed at Impact	Subset Frequency	Subset Percent	Other Frequency	Other Percent	Odds Ratio	Max Gain
31 to 35 MPH	777	6.73	15166	6.53	1.031	23.197
36 to 40 MPH	761	6.59	13634	5.87	1.123*	83.342
41 to 45 MPH	1601	13.87	20349	8.76	1.583*	589.583
46 to 50 MPH	882	7.64	10023	4.32	1.770*	383.822
51 to 55 MPH	1586	13.74	16104	6.93	1.981*	785.575
56 to 60 MPH	942	8.16	7100	3.06	2.669*	589.105
61 to 65 MPH	822	7.12	8283	3.57	1.997*	410.306
66 to 70 MPH	753	6.52	9410	4.05	1.610*	285.290
71 to 75 MPH	269	2.33	1801	0.78	3.005*	179.484
76 to 80 MPH	322	2.79	988	0.43	6.557*	272.893
81 to 85 MPH	133	1.15	315	0.14	8.495*	117.343
86 to 90 MPH	102	0.88	231	0.10	8.884*	90.518
91 to 95 MPH	27	0.23	49	0.02	11.086*	24.565
96 to 100 MPH	77	0.67	133	0.06	11.648*	70.389
Over 100 MPH	40	0.35	86	0.04	9.358*	35.725

It should be noted that the speed limit on country roads is generally 45 MPH. All speeds above 40 MPH are dramatically over-represented, and the over-representation increases with the increase in impact speeds, from about 1.6 at 45 MPH to 11.6 at 100 MPH.

The next cross-tabulation quantifies how this relates to the severity of the crash for ID crashes.

Severity by Impact Speed

The following display presents information on the effect of increased impact speed on the severity of the crash.

CARE 10.1.0.19 - [Crosstab Results - 2014-2017 Alabama Integrated Crash Data - Filter = FY2015-20...

File Dashboard Filters Analysis Crosstab Locations Tools Window Help

2014-2017 Alabama Integrated Crash Data | FY2015-2017 AND DUI | 1/ 1/2014 | 10/16/2017

Suppress Zero Values: None | Select Cells: | Column: Crash Severity ; Row: CU Estimated Speed at Impact

	Fatal Injury	Incapacitating Injury	Non-Incapacitating Inju	Possible Injury	Property Damage Only	Unknown	TOTAL
0 MPH	1 0.16%	0 0.00%	0 0.00%	0 0.00%	4 0.04%	0 0.00%	5 0.03%
1 to 5 MPH	3 0.48%	16 0.74%	29 0.94%	25 1.49%	319 3.08%	2 0.44%	394 2.15%
6 to 10 MPH	4 0.65%	27 1.25%	32 1.04%	34 2.03%	332 3.21%	8 1.77%	437 2.38%
11 to 15 MPH	4 0.65%	14 0.65%	36 1.17%	34 2.03%	249 2.40%	3 0.66%	340 1.85%
16 to 20 MPH	1 0.16%	23 1.06%	35 1.14%	39 2.33%	250 2.41%	3 0.66%	351 1.91%
21 to 25 MPH	2 0.32%	37 1.71%	42 1.37%	37 2.21%	307 2.96%	5 1.11%	430 2.34%
26 to 30 MPH	2 0.32%	41 1.89%	57 1.85%	43 2.56%	343 3.31%	5 1.11%	491 2.68%
31 to 35 MPH	7 1.13%	65 3.00%	105 3.42%	80 4.77%	510 4.93%	10 2.21%	777 4.24%
36 to 40 MPH	5 0.81%	92 4.25%	134 4.36%	76 4.53%	444 4.29%	10 2.21%	761 4.15%
41 to 45 MPH	29 4.68%	205 9.46%	281 9.14%	141 8.41%	924 8.92%	21 4.65%	1601 8.73%
46 to 50 MPH	25 4.03%	137 6.32%	188 6.12%	71 4.23%	455 4.39%	6 1.33%	882 4.81%
51 to 55 MPH	65 10.48%	283 13.06%	362 11.78%	97 5.78%	762 7.36%	17 3.76%	1586 8.65%
56 to 60 MPH	40 6.45%	191 8.81%	220 7.16%	57 3.40%	418 4.04%	16 3.54%	942 5.13%
61 to 65 MPH	52 8.39%	186 8.58%	163 5.30%	51 3.04%	358 3.46%	12 2.65%	822 4.48%
66 to 70 MPH	47 7.58%	**132** **6.09%**	144 4.68%	43 2.56%	372 3.59%	15 3.32%	753 4.10%
71 to 75 MPH	34 5.48%	62 2.86%	49 1.59%	18 1.07%	104 1.00%	2 0.44%	269 1.47%
76 to 80 MPH	**41** **6.61%**	71 3.28%	75 2.44%	18 1.07%	113 1.09%	4 0.88%	322 1.76%
81 to 85 MPH	18 2.90%	27 1.25%	29 0.94%	8 0.48%	49 0.47%	2 0.44%	133 0.72%
86 to 90 MPH	14 2.26%	25 1.15%	29 0.94%	6 0.36%	27 0.26%	1 0.22%	102 0.56%
91 to 95 MPH	8 1.29%	6 0.28%	5 0.16%	1 0.06%	6 0.06%	1 0.22%	27 0.15%
96 to 100 MPH	15 2.42%	21 0.97%	15 0.49%	7 0.42%	16 0.15%	3 0.66%	77 0.42%
Over 100 MPH	13 2.10%	13 0.60%	4 0.13%	1 0.06%	8 0.08%	1 0.22%	40 0.22%
E Stationary	3 0.48%	11 0.51%	14 0.46%	11 0.66%	49 0.47%	4 0.88%	92 0.50%
Unknown	152 24.52%	426 19.66%	945 30.74%	728 43.41%	3715 35.88%	269 59.51%	6235 33.99%
Not Applicable	2 0.32%	21 0.97%	41 1.33%	42 2.50%	209 2.02%	28 6.19%	343 1.87%
CU is Not a Vehicle	33 5.32%	32 1.48%	31 1.01%	9 0.54%	4 0.04%	4 0.88%	113 0.62%
CU is Unknown	0 0.00%	3 0.14%	9 0.29%	0 0.00%	8 0.08%	0 0.00%	20 0.11%
TOTAL	620 3.38%	2167 11.81%	3074 16.76%	1677 9.14%	10355 56.45%	452 2.46%	18345 100.00%

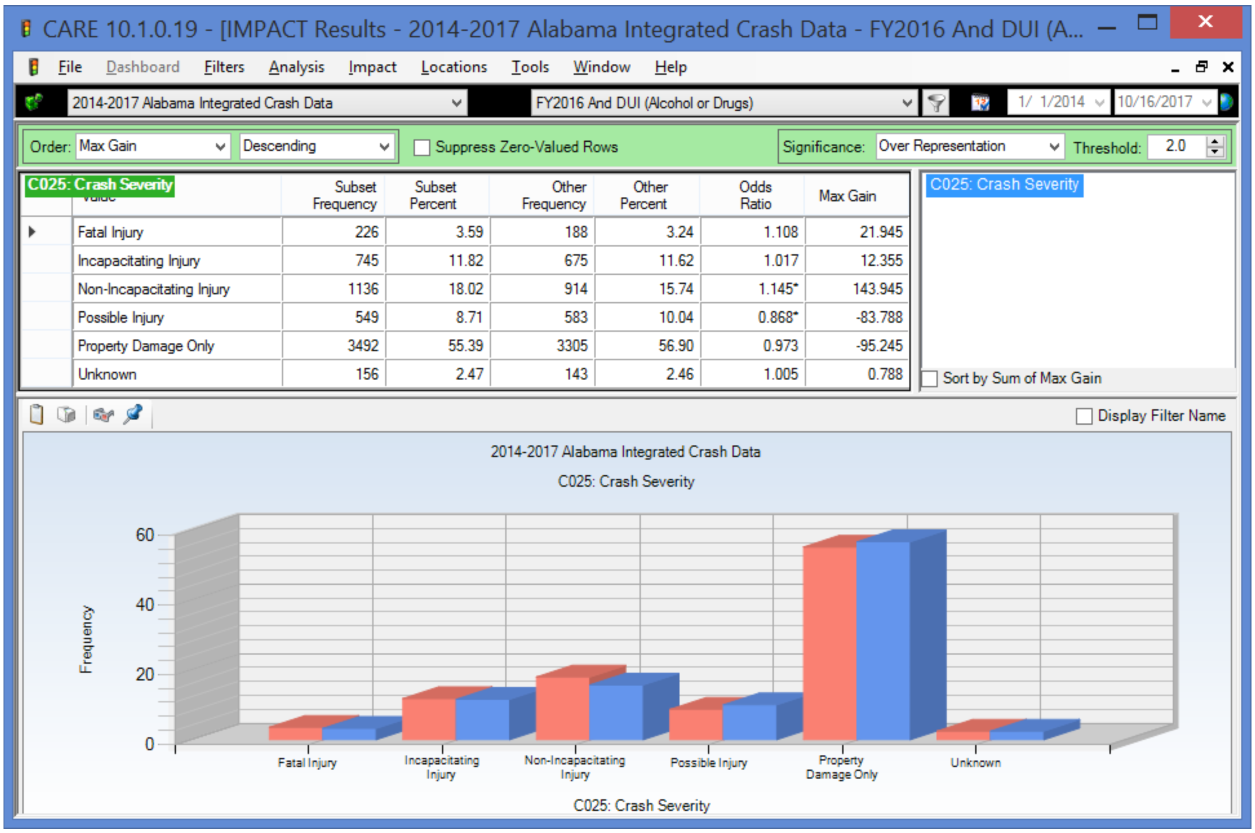
Notice the red in the fatality and severe injury cells as speeds increase. What is more enlightening is the probability that the crash results in a fatality as a function of impact speed. In the 41-45 MPH impact speed the probability is only a little over one in every 55 crashes. As impact speeds climb to the 51-55 MPH, this probability more than doubles to one in about 24 crashes. At 61-65 MPH it increases again (exponentially) to one in about every 16 crashes, and at 71-75 it is about one in eight, which is about double again. For above 90 MPH it is about one in 4 crashes.

The rule of thumb is that for every 10 MPH increase in speeds, the probability of the crash being fatal doubles. Conversely, a reduction in impact speeds by 10 MPH would cut the number of fatal crashes in half. This is the reason that selective enforcement is effective. However, there is another major factor in effect as well – the failure of ID drivers to be properly restrained, which will be covered in a separate attribute below (Restraint Use by Impaired Drivers).

It was found in a comparison of the first 9 months of 2017 vs. 2016 that there was a dramatic decrease in fatalities caused by ID. Further analyses determined the reason for this was the reduction in impact speeds. In FY2016, 54.3% of the impact speeds were 50 MPH or above; in FY2017 this number was reduced to 50.3%. This reduction in impact speeds for ID crashes is the major cause of the reduction in ID fatality crashes in FY2017 as shown in the next section.

Severity of ID Crashes Comparing FY2016 vs FY2017

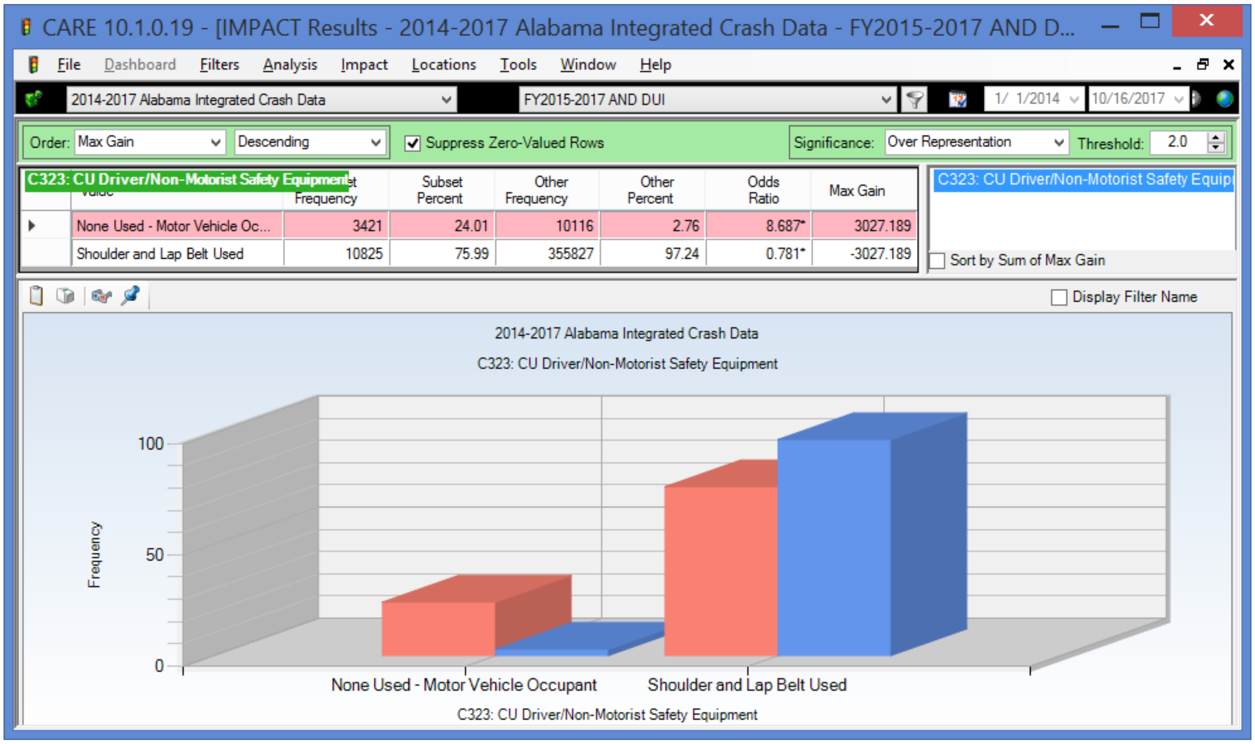
The following display shows the reduction in FY2017 (Other, blue bars) that occurred as compared to FY2016 (Subset, red bars). The reduction was from 226 to 188, which was a 16.8% reduction in ID fatal crashes. The proportions do not show as dramatic a decrease since the overall number of ID crashes also was also down significantly, from a total of 6304 crashes (all severities) to 5808, which was a 7.9% overall decrease. So both the overall crashes and the fatality crashes were reduced, but the reduction in the fatality crashes were obviously much greater than that of the overall crashes.



C025: Crash Severity	Subset Frequency	Subset Percent	Other Frequency	Other Percent	Odds Ratio	Max Gain
Fatal Injury	226	3.59	188	3.24	1.108	21.945
Incapacitating Injury	745	11.82	675	11.62	1.017	12.355
Non-Incapacitating Injury	1136	18.02	914	15.74	1.145*	143.945
Possible Injury	549	8.71	583	10.04	0.868*	-83.788
Property Damage Only	3492	55.39	3305	56.90	0.973	-95.245
Unknown	156	2.47	143	2.46	1.005	0.788

Restraint Use by Impaired Drivers

The following display presents a comparison of ID driver safety belt use against those who were not ID in the same time period.



Risk-taking involved in ID does not stop with excess speed; it extends to not being properly restrained. The above analysis demonstrates that the impaired driver is close to nine (8.687) times more likely to be unrestrained as in the non-ID crash. The next analysis demonstrates how this contributes to fatality crashes.

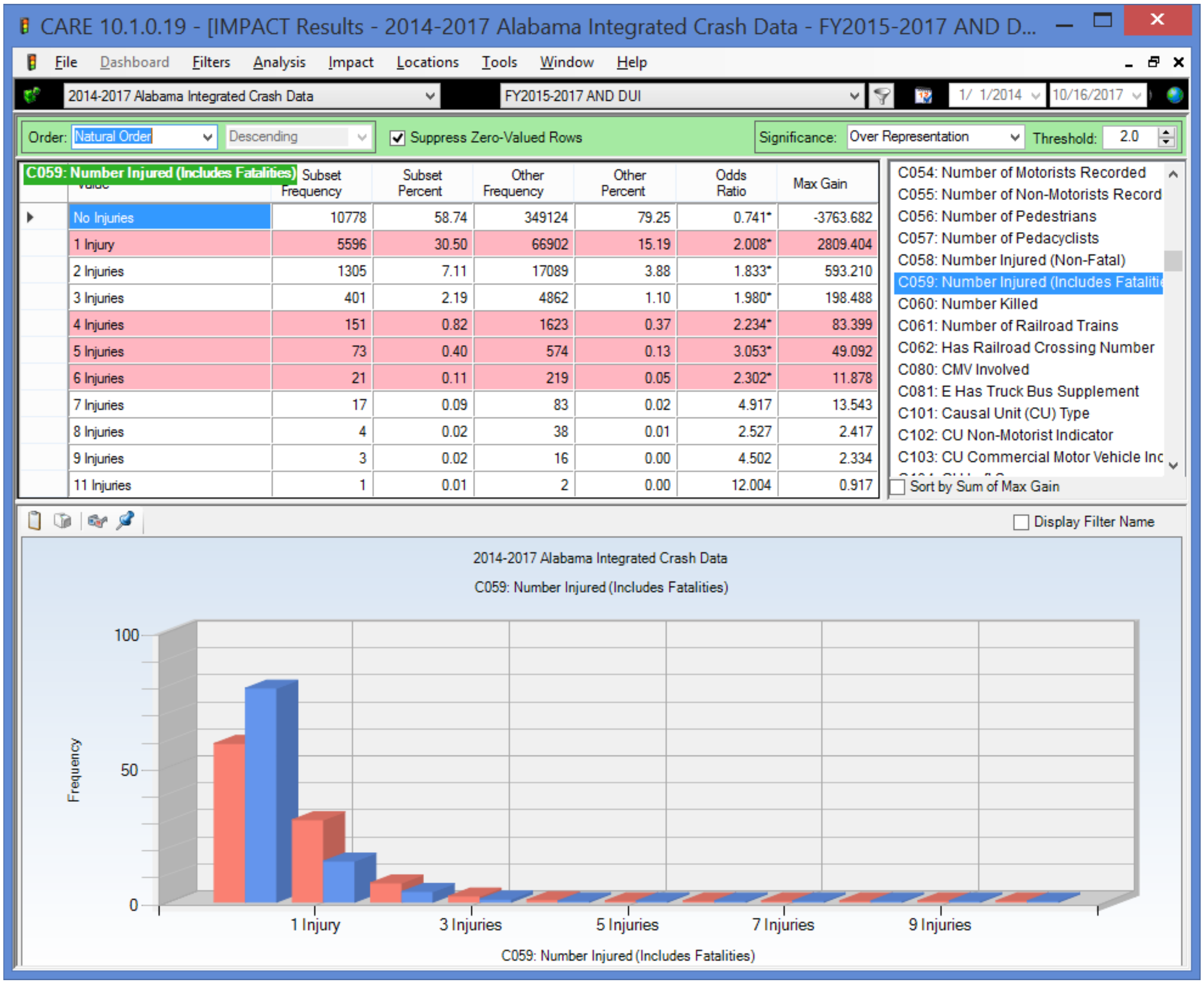
Fatality Crashes by Restraint Use for Impaired Drivers

	Fatal Injury	Incapacitating Injury	Non-Incapacitating Inju	Possible Injury	Property Damage Only	Unknown	TOTAL
None Used - Motor Vehicle Oc	326 52.67%	868 40.43%	798 25.99%	240 14.38%	1136 11.03%	53 11.73%	3421 18.74%
Shoulder and Lap Belt Used	177 28.59%	933 43.46%	1707 55.60%	1082 64.83%	6753 65.58%	173 38.27%	10825 59.30%

A comparison of the probability of a fatal crash indicates that a fatality is almost six (5.82) times more likely if the impaired driver is not using proper restraints. The probability is estimated by 326 fatality crashes out of 3,421 when restraints were not used (=1 in 10.5), as opposed to only 177 fatal crashes out of 10,825 crashes when restraints were used (1 in 61.2). So the combined effect of lower restraint use and higher speed is a devastating combination that accounts for the high lethality of ID crashes. But that is not all; see the following three items for additional related information.

Number Injured (Including Fatalities)

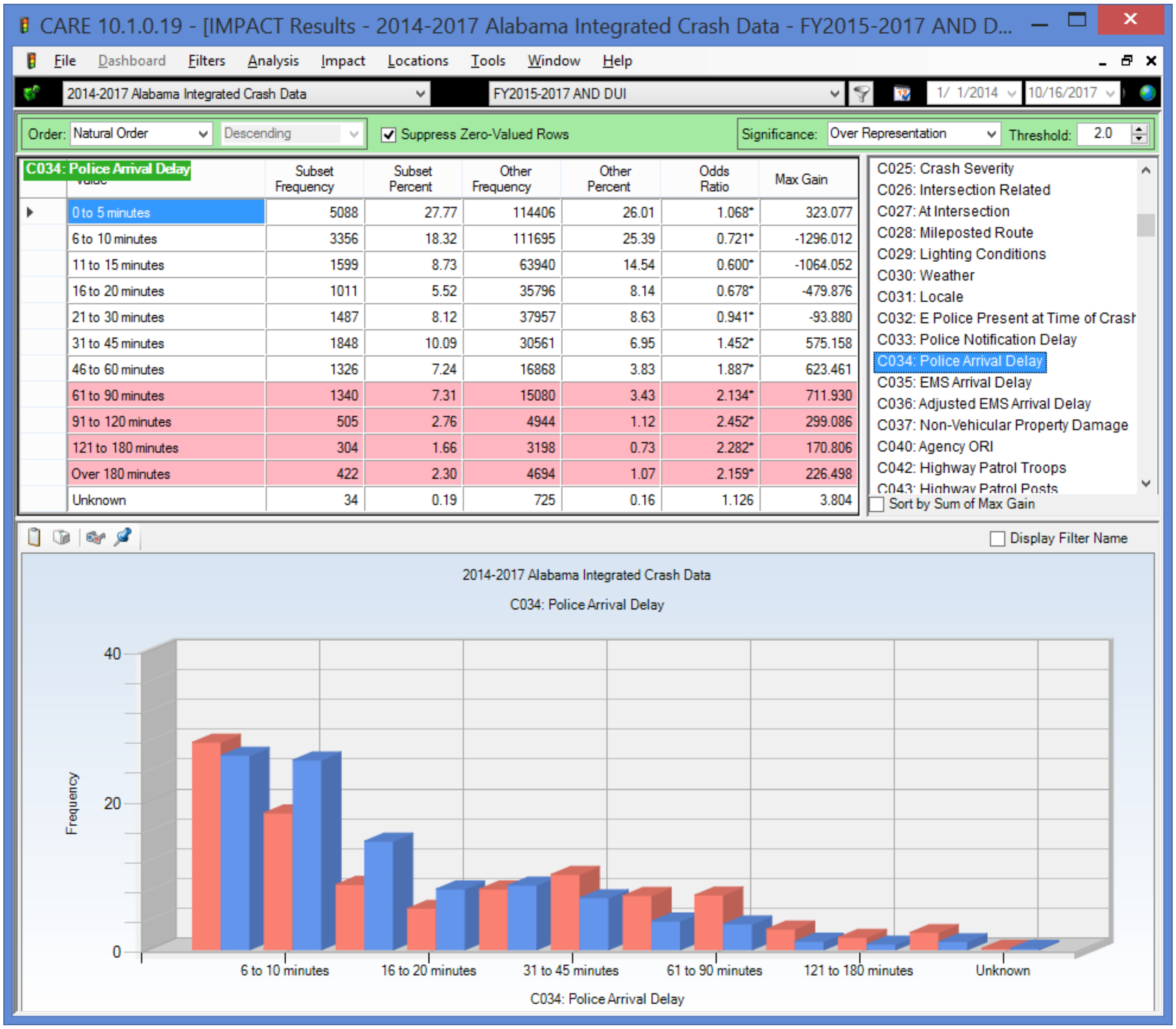
The following display presents a comparison of ID crash number of injuries against number of injuries in crashes that were not ID in the same time period.



C059: Number Injured (Includes Fatalities)	Subset Frequency	Subset Percent	Other Frequency	Other Percent	Odds Ratio	Max Gain
No Injuries	10778	58.74	349124	79.25	0.741*	-3763.682
1 Injury	5596	30.50	66902	15.19	2.008*	2809.404
2 Injuries	1305	7.11	17089	3.88	1.833*	593.210
3 Injuries	401	2.19	4862	1.10	1.980*	198.488
4 Injuries	151	0.82	1623	0.37	2.234*	83.399
5 Injuries	73	0.40	574	0.13	3.053*	49.092
6 Injuries	21	0.11	219	0.05	2.302*	11.878
7 Injuries	17	0.09	83	0.02	4.917	13.543
8 Injuries	4	0.02	38	0.01	2.527	2.417
9 Injuries	3	0.02	16	0.00	4.502	2.334
11 Injuries	1	0.01	2	0.00	12.004	0.917

The above shows that not only are ID crashes more severe to those injured, but also the number of multiple injuries in these ID crashes is over-represented as well. Some might suspect that an ID crash might involve just a driver returning home from a night of indulgence. However, rarely is the impaired driver alone, and, of course, if another vehicle is involved, then that would also generally increase the number of injuries. It is interesting that all of the multiple-injury categories are over-represented.

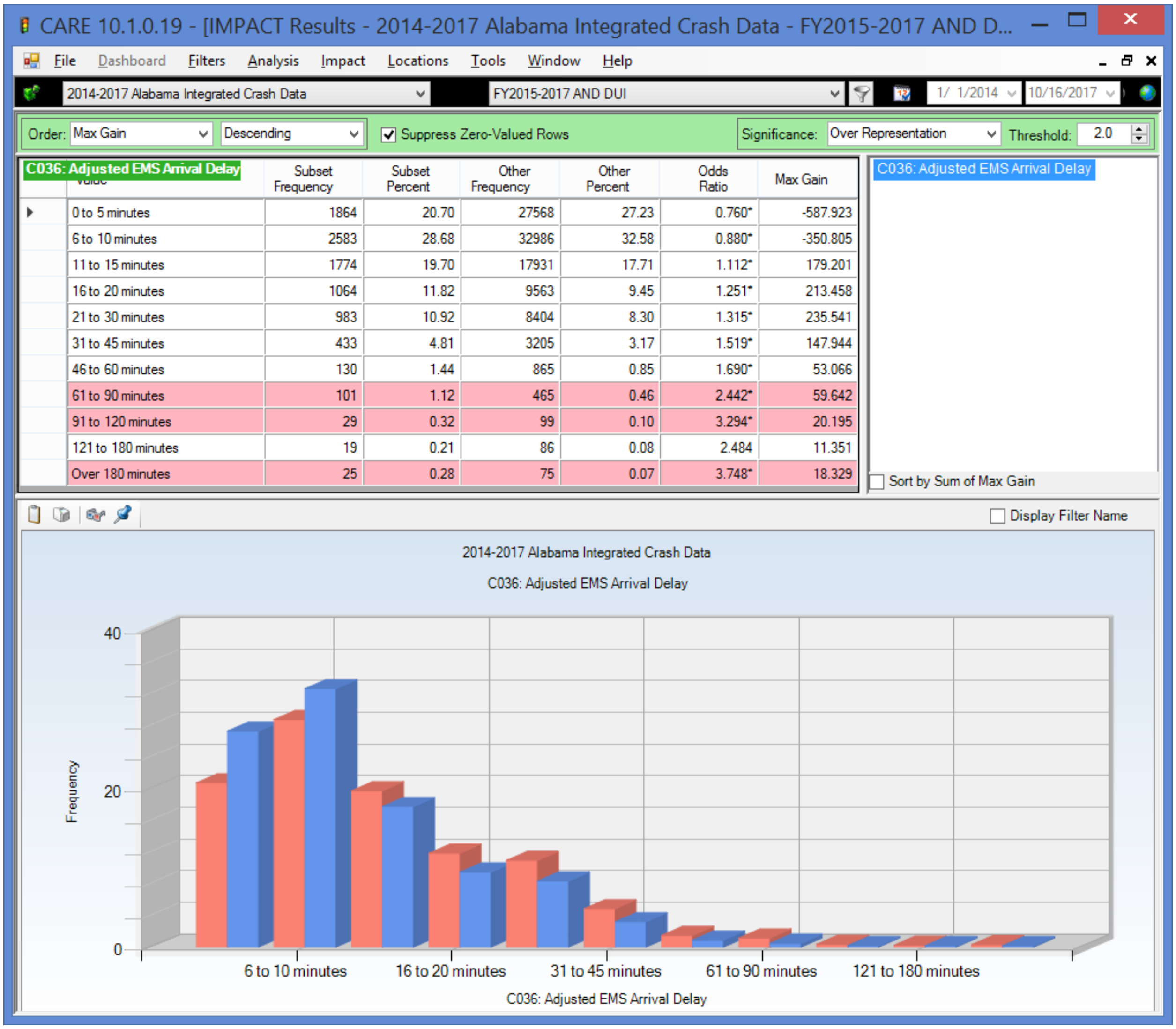
Police Arrival Delay



C034: Police Arrival Delay	Subset Frequency	Subset Percent	Other Frequency	Other Percent	Odds Ratio	Max Gain
0 to 5 minutes	5088	27.77	114406	26.01	1.068*	323.077
6 to 10 minutes	3356	18.32	111695	25.39	0.721*	-1296.012
11 to 15 minutes	1599	8.73	63940	14.54	0.600*	-1064.052
16 to 20 minutes	1011	5.52	35796	8.14	0.678*	-479.876
21 to 30 minutes	1487	8.12	37957	8.63	0.941*	-93.880
31 to 45 minutes	1848	10.09	30561	6.95	1.452*	575.158
46 to 60 minutes	1326	7.24	16868	3.83	1.887*	623.461
61 to 90 minutes	1340	7.31	15080	3.43	2.134*	711.930
91 to 120 minutes	505	2.76	4944	1.12	2.452*	299.086
121 to 180 minutes	304	1.66	3198	0.73	2.282*	170.806
Over 180 minutes	422	2.30	4694	1.07	2.159*	226.498
Unknown	34	0.19	725	0.16	1.126	3.804

ID crashes generally had longer police arrival delays; in this case all arrival delays over 30 minutes were over-represented. There can be little doubt that this has to do with the rural nature of these crashes and the potential that at night they would not be discovered for some time. The analysis below shows how this impacts EMS arrival time, which is a comparison of crashes that include injuries, and thus would generally call for an EMS response.

EMS Arrival Delay



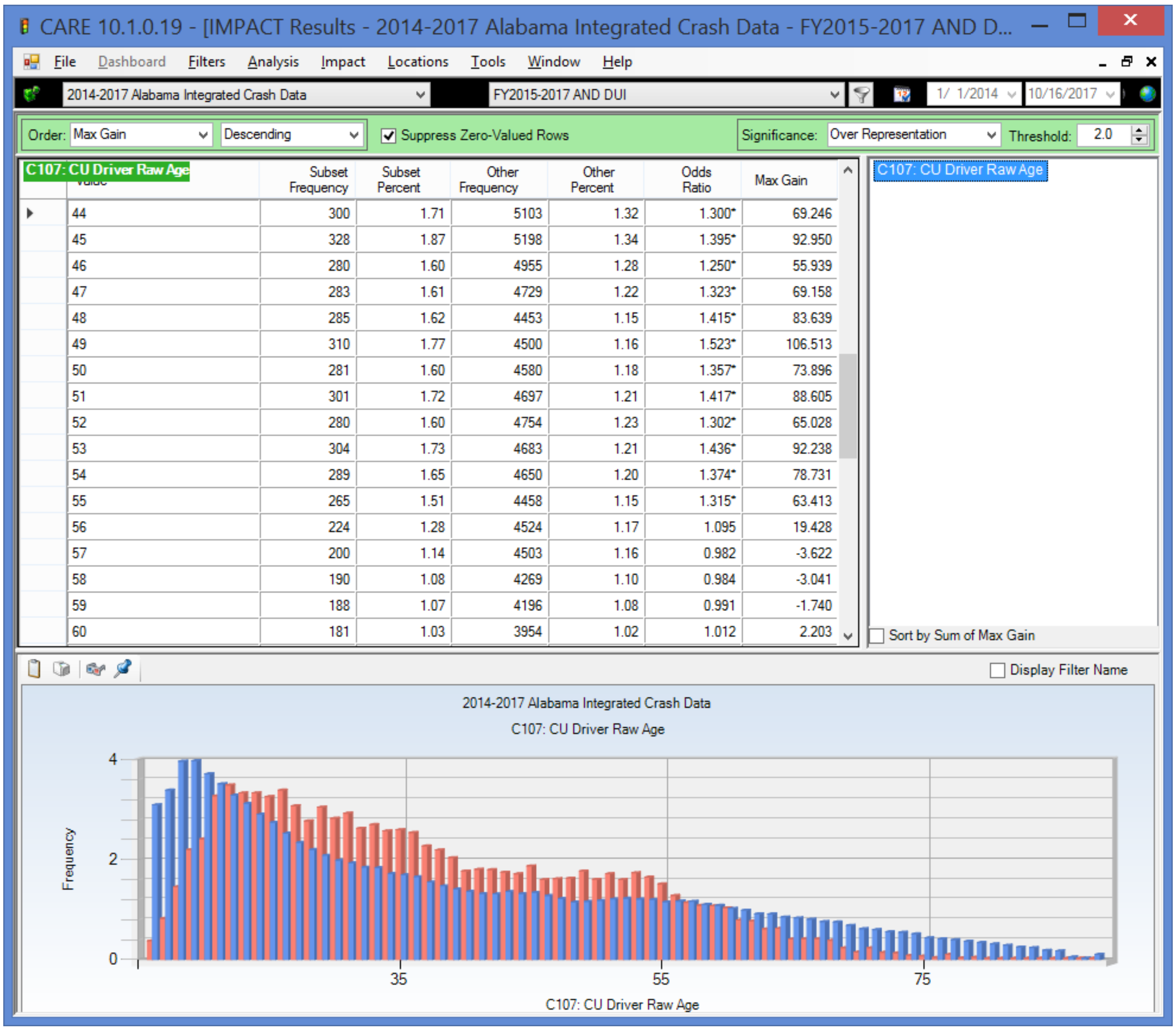
C036: Adjusted EMS Arrival Delay Value	Subset Frequency	Subset Percent	Other Frequency	Other Percent	Odds Ratio	Max Gain
0 to 5 minutes	1864	20.70	27568	27.23	0.760*	-587.923
6 to 10 minutes	2583	28.68	32986	32.58	0.880*	-350.805
11 to 15 minutes	1774	19.70	17931	17.71	1.112*	179.201
16 to 20 minutes	1064	11.82	9563	9.45	1.251*	213.458
21 to 30 minutes	983	10.92	8404	8.30	1.315*	235.541
31 to 45 minutes	433	4.81	3205	3.17	1.519*	147.944
46 to 60 minutes	130	1.44	865	0.85	1.690*	53.066
61 to 90 minutes	101	1.12	465	0.46	2.442*	59.642
91 to 120 minutes	29	0.32	99	0.10	3.294*	20.195
121 to 180 minutes	19	0.21	86	0.08	2.484	11.351
Over 180 minutes	25	0.28	75	0.07	3.748*	18.329

For much the same reasons as the longer police arrival delays, EMS delays were over-represented for impaired driving crashes in all categories above ten minutes, and dramatically for the very longer times of 61 minutes and above (indicated by the red background in the table). This obviously contributes to the severity of crashes and the chances that the crash results in one or more fatalities. As for the very long times, these might be due to the delay in discovering the crash since they generally over-represented late night in rural locations.

Driver and Vehicle Demographics

Driver Age

The following display presents a comparison of ID crash causal driver age against the same for crashes that were not ID in the same time period.

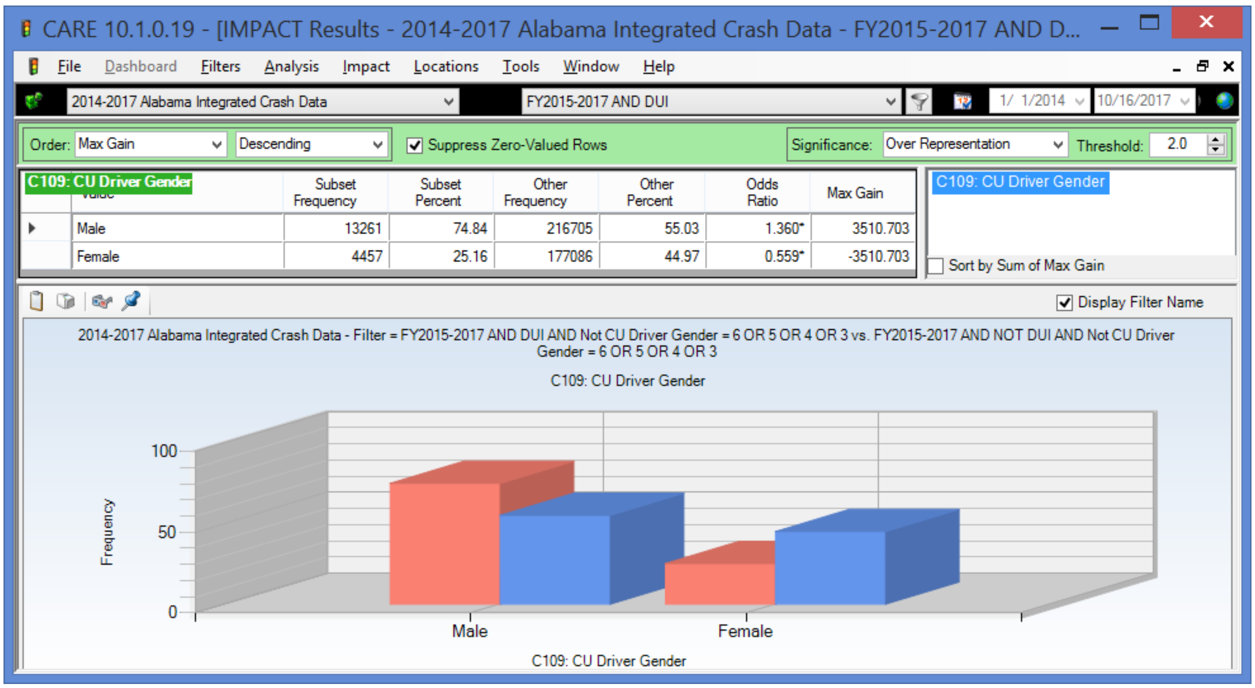


C107: CU Driver Raw Age Value	Subset Frequency	Subset Percent	Other Frequency	Other Percent	Odds Ratio	Max Gain
44	300	1.71	5103	1.32	1.300*	69.246
45	328	1.87	5198	1.34	1.395*	92.950
46	280	1.60	4955	1.28	1.250*	55.939
47	283	1.61	4729	1.22	1.323*	69.158
48	285	1.62	4453	1.15	1.415*	83.639
49	310	1.77	4500	1.16	1.523*	106.513
50	281	1.60	4580	1.18	1.357*	73.896
51	301	1.72	4697	1.21	1.417*	88.605
52	280	1.60	4754	1.23	1.302*	65.028
53	304	1.73	4683	1.21	1.436*	92.238
54	289	1.65	4650	1.20	1.374*	78.731
55	265	1.51	4458	1.15	1.315*	63.413
56	224	1.28	4524	1.17	1.095	19.428
57	200	1.14	4503	1.16	0.982	-3.622
58	190	1.08	4269	1.10	0.984	-3.041
59	188	1.07	4196	1.08	0.991	-1.740
60	181	1.03	3954	1.02	1.012	2.203

The blue (non-ID) bars illustrate the problems that 16-20 year old drivers have in general. On the bright side, these issues are not generally caused by ID up until ages 19 and 20, and even at these ages they are under-represented. The first age with a significant over-representation starts at age 24 and continues on to age 55. It is clear that the legal drinking age is having a very positive effect on keeping the numbers down for the 16-20 year old drivers, and any attempt to decrease this legal age should be fought strenuously by the traffic safety professionals despite evidence to the contrary presented by other disciplines.

There is a bi-modal distribution in the 21-55 year olds; 21 through about 35, and a second group from 36 to 54. Generally the first of these might be classified as social drinkers. However, it is hard to escape the fact that those who are in their late 30s up through their middle ages would not be largely problem drinkers. Countermeasures for these two groups will typically be quite different.

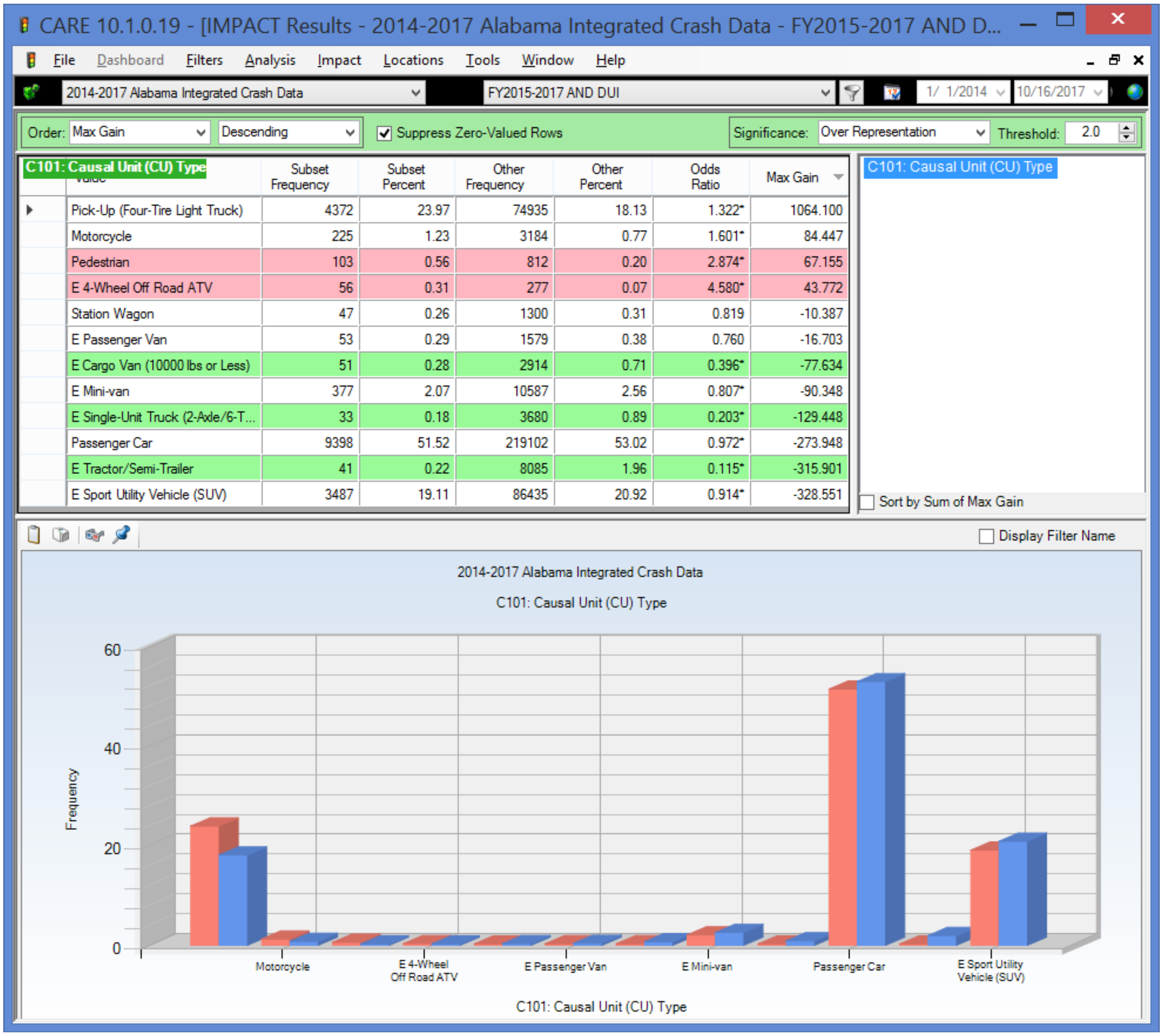
Impaired Driver Gender



The red bars and the blue bars each sum to 100%. So the breakdown in male IS causal drivers is 74.84% male and 25.16% female. For non-ID, the percentage is 55.03 male and 44.97 female. These differences certainly indicate that males are a far greater issue, and if there are countermeasures that can be directed toward them, doing so would be much more cost-effective, all other things being equal.

Causal Vehicle Types with 30 or more Crashes

The following display presents a comparison of ID crash causal unit type against the same for crashes that were not ID in the same time period.



C101: Causal Unit (CU) Type	Subset Frequency	Subset Percent	Other Frequency	Other Percent	Odds Ratio	Max Gain
Pick-Up (Four-Tire Light Truck)	4372	23.97	74935	18.13	1.322*	1064.100
Motorcycle	225	1.23	3184	0.77	1.601*	84.447
Pedestrian	103	0.56	812	0.20	2.874*	67.155
E 4-Wheel Off Road ATV	56	0.31	277	0.07	4.580*	43.772
Station Wagon	47	0.26	1300	0.31	0.819	-10.387
E Passenger Van	53	0.29	1579	0.38	0.760	-16.703
E Cargo Van (10000 lbs or Less)	51	0.28	2914	0.71	0.396*	-77.634
E Mini-van	377	2.07	10587	2.56	0.807*	-90.348
E Single-Unit Truck (2-Axle/6-T...	33	0.18	3680	0.89	0.203*	-129.448
Passenger Car	9398	51.52	219102	53.02	0.972*	-273.948
E Tractor/Semi-Trailer	41	0.22	8085	1.96	0.115*	-315.901
E Sport Utility Vehicle (SUV)	3487	19.11	86435	20.92	0.914*	-328.551

Vehicles types with less than 30 crashes in the ID dataset were removed for the above display, and pedestrians were considered a unit type. While pickups have the highest MaxGain indicting the greatest potential for reduction, Motorcycles, Pedestrian and ATVs all have higher over-representations but their MaxGain is lower because of their lower frequencies. Of interest is the proportion of pedestrians and off road 4-wheelers that involve ID, both of which are over two times their expected proportion. So the major finding of this analysis is that motorcycle, pedestrian and 4-wheeler crashes have far more than their share of ID causation.

Driver License Status

CARE 10.1.0.19 - [IMPACT Results - 2014-2017 Alabama Integrated Crash Data - FY2015-2017 AND D...

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2014-2017 Alabama Integrated Crash Data | FY2015-2017 AND DUI | 1/ 1/2014 | 10/16/2017

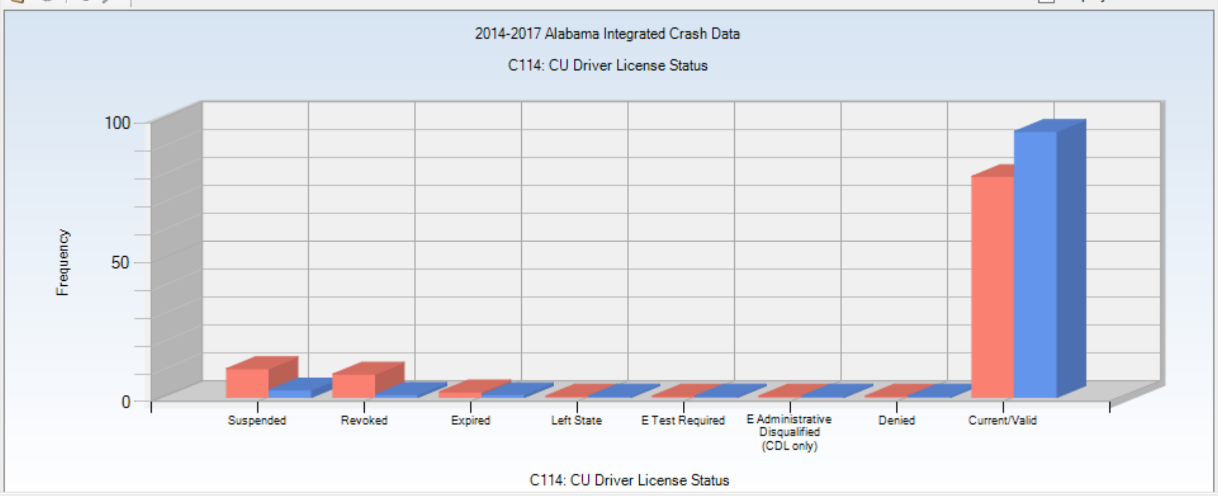
Order: Max Gain | Descending | Suppress Zero-Valued Rows | Significance: Over Representation | Threshold: 2.0

C114: CU Driver License Status	Subset Frequency	Subset Percent	Other Frequency	Other Percent	Odds Ratio	Max Gain
Suspended	1579	10.26	9738	2.64	3.891*	1173.227
Revoked	1280	8.31	3786	1.02	8.114*	1122.241
Expired	300	1.95	3537	0.96	2.036*	152.617
Left State	30	0.19	112	0.03	6.428*	25.333
E Test Required	8	0.05	82	0.02	2.341	4.583
E Administrative Disqualified (C...	1	0.01	8	0.00	3.000	0.667
Denied	5	0.03	136	0.04	0.882	-0.667
Current/Valid	12191	79.19	352036	95.29	0.831*	-2478.000

C114: CU Driver License Status

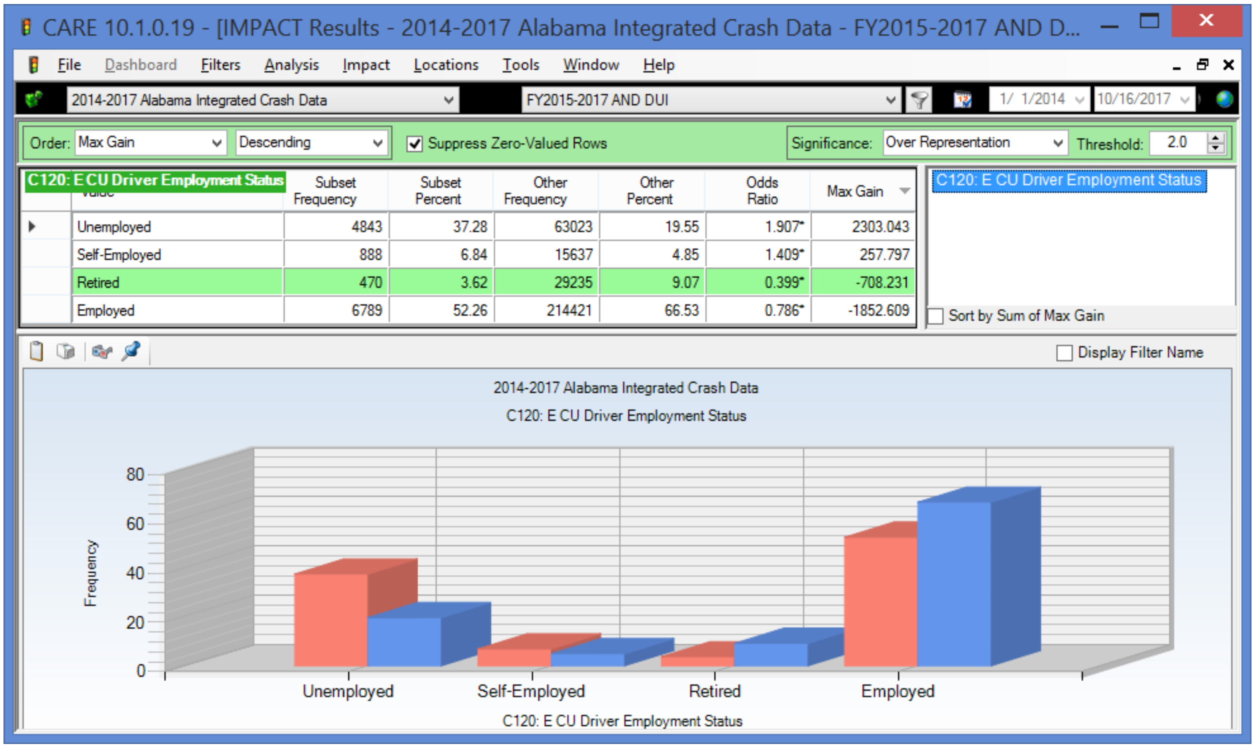
Sort by Sum of Max Gain

Display Filter Name



Clearly ID crashes are so over-represented in ID causal drivers without legitimate licenses that the question might be asked: Does suspending or revoking their licenses even make a difference? Some states have gone so far as to make it a mandatory arrest if a driver is found to not have a current license. The results of this analysis need to be given serious consideration by those determining the direction of the legislative process regarding ID. It seems clear that the suspension/revocation of licenses is not bringing about the desired effect.

Driver Employment Status



In our current era when the economy is playing such a big role in traffic safety, the quantification and tracking of the employment proportion of drivers involved in ID crashes will be important. This indicates that their unemployment rate is about 90.7% higher than expected. This is probably not unexpected, and the correlation between not having a job and being involved in an ID crash should be watched carefully going forward in that it could affect the type and location for countermeasures.

Summary of Findings

The following summarizes the findings of the problem identification analyses given above:

- **General Comparison of FY2017 against FY2015-2016**
    - Overall crash frequencies got FY2017 were about 5000 crashes higher than the average of FY2015-2016. Total crashes in FT2017 were only about 1560 fewer than in FY2016. Thus, there is nothing in the overall crash picture that would suggest that FY2017 should not be comparable to FY2015-2016, or even to FY2016 alone.
    - In a comparison of the fiscal years, overall fatal crashes were up by 22.8% in FY2016 over FY2015, and this only came down by 2.1% in FY2017.
    - A similar a comparison of the fiscal years of ID fatal crashes showed an increase of 9.2% in FY2016 over FY2015, and this only came down by 1.7% in FY2017.
    - On the other hand, there was a remarkable decrease in the proportion of fatal crashes caused by ID to the overall number of fatal crashes for each year. Over the three fiscal year periods (FY2015-2017), the proportions were 27.0%, 24.0% and 20.4%, a significant overall reduction of reported ID fatal crashes of 6.6%. The reason for this was given intensive analysis in the Factors Affecting Severity Section.

- **Geographical Factors**
    - County - Generally, the over-represented counties are those with combined large population centers and large rural areas, as opposed to the highly urbanized counties or the extremely rural counties. One reason that the highly urbanized counties are under-represented is the large number of low severity crashes that occur there separate and apart from ID crashes. See the rural-urban comparison below.
    - Rural Areas with the Greatest Increases in FY2017 – several virtual cities (rural areas of counties) were found to have over twice the proportion of ID crashes compared to their proportions in FY2015-2016. Place in Max Gain order, the ones with the highest potential for reduction were (all rural areas of the following counties): Cullman, Blount, Houston, Coffee, Colbert, and Pike.
    - City Comparisons of ID crashes by Total ID Crash Frequency. There is little surprise in this output, which tracks the areas by population. Traffic safety professionals should look for any locations that fall counter to this trend.
    - City (and area) Comparisons within Crash Frequency Ranges – analyses were performed for those areas that had 100-200 ID crashes as well as those that had 60-100 ID crashes. There are presented separately to present fair comparisons among the various areas.
    - Overall Area Comparisons Conclusions –Generally those rural areas that are adjacent to (or contain) significant urbanized areas are over-represented, since their urban areas generate more traffic even in the rural areas. Possible factors for relatively fewer severe ID crashes within urban areas include:

        - Less need for motor vehicle travel and shorter distances to the drinking establishments;
        - Larger police presence in the metropolitan areas; and
        - Lower speeds in rural areas.
    - The city, county, and area comparisons are, of necessity, a selection of the total outputs that could be generated. They are given to illustrate the capabilities as much as to present the numerical results. Anyone wishing additional studies or outputs, please contact CAPS – see e-mail address above.
    - Severity of Crash by Rural-Urban – While only about 42% of crashes occur in rural areas, nearly 67% of the fatal crashes occur there. Similar results are found for the highest severity non-fatal crashes. This is obviously the result of higher impact speeds in the rural areas. Note that additional causes of increased severity are given in the Factors Affecting Severity Section.
    - Rural or Urban ID Crash Frequency – Not only are impaired driving crashes more severe in rural areas, but their frequency is about the same as in the urban area, despite the much lower population and traffic volumes (about 42% rural as compared to about 58% urban). While only 22.44% of the crashes are expected in the rural areas, the proportion of crashes in the rural areas is over 42.14%, or very close to double its expected value (Odds Ratio = 1.965).
    - Highway Classifications – County roads had well over twice their expected proportion of crashes, while all other roadway classifications were under-represented. County road characteristics no doubt contribute to the crash frequency. County roads are also known to be less "crashworthy" (i.e., they result in more severe crashes at comparable impact speeds).
    - Locale – Reflecting the rural over-representation, open country and residential roadways show a high level of over-representation as compared with the more urbanized area types, especially Shopping or Business, which only has about half of its expected proportion.

- **Time Factors**
    - Year – a discussion of the overall crash, fatal crash and ID fatal crash frequencies by year were given in the section above entitled IS Update for FY2017 that appears right after the Introduction. The display in the Year attribute section presents and discusses the three fiscal years according to their calendar year occurrences.
    - Month – There only significant over-representations by month was in February and March, indicating that the number of ID crashes correlated well with the other crashes during the rest of the months. None of the months were significantly under-represented.
    - Day of the Week – This analysis is not only useful for the typical work week, but it also reflects the typical "holiday weekend" patterns. The days can be classified as follows:

        - Typical work weekday (Monday through Thursday) – these days are under-represented in ID crashes due to the need for many to go to work the following day.
        - Friday – this pattern is also reflected in the day before a weekend (or holiday), i.e., before a day off. The high ID frequency on this day is due to those who are getting an early start to the weekend, recognizing that they have no work responsibilities the following day.
        - Saturday – the "Saturday" pattern is the worse for ID crashes in that it has both an early morning component (like Sunday) and a late night component (like Friday). So, it could be viewed as a combination of the typical Friday and Sunday.
        - Sunday – since this is the last day of a holiday sequence or weekend, its over-representation comes strictly from those who start on Saturday night and do not complete their use of alcohol/drugs until after midnight.
    - "Holiday Weekends" – these can be viewed as a sequence of the weekend-pattern sequence. For example, the Wednesday before Thanksgiving would follow the Friday pattern assuming that most are at work on Wednesday. The Thursday, Friday and Saturday would follow the Saturday pattern, and the Sunday at the end of the weekend would follow the typical Sunday pattern. This is the reason that long holiday events (i.e., several days off) can be much more prone to ID crashes than the typical weekend. Three-day weekends typically give Monday off, so that Monday would behave like the typical Sunday, and both the Saturday and Sunday would follow the Saturday pattern.
    - Time of Day – The extent to which night-time hours are over-represented is quite striking. Optimal times for ID enforcement would start immediately following any rush hour details, and would continue through at least 3 AM.
    - Time of Day by Day of the Week – This quantifies the extent of the crash concentrations on Friday nights, Saturday mornings and Saturday nights and early Sunday mornings. This is a very useful summary for deploying selective enforcement details.

- **Factors Affecting Severity**
    - ID Crash Severity -- The rate of injuries and fatalities are consistently higher in ID crashes than that of non-ID crashes. Fatality crashes are over seven times their expected proportion, while the two highest non-fatal injury classifications have over twice their expected values when compared with non-impaired driving crashes The odds ratio is over three (3.204) for the highest non-fatal classification, Incapacitation Injury. The other variables analyzed in this section give the reasons for this disparity.
    - Speed at Impact – All impact speeds above 45 MPH are dramatically over-represented. See the next attribute.

- Severity by Impact Speed –Past analyses have found the general rule of thumb that for every 10 MPH increase in speeds, the probability of the crash being fatal doubles. This was validated in the discussion of the cross-tabulation.
- Severity Comparison FY2017 vs FY2016 – There was a reduction from 226 in FY2016 to 188 in FY2017, which was a 16.8% reduction in ID fatal crashes. Both the overall crashes and the fatality crashes were reduced, but the reduction in the fatality crashes were obviously much greater than that of the overall crashes.
- Restraint Use by Impaired Drivers – The impaired drivers are close to 9 times more likely to be unrestrained than the non-ID causal drivers. Clearly ID drivers lose a good part of their concept of risk when they are willing to drive while being impaired.
- Fatality Crashes by Restraint Use for Impaired Drivers – A comparison of the probability of a fatal crash indicates that a fatality is almost six (5.82) times more likely if the impaired driver is not using proper restraints. With restraints, one in 61 ID crashes are fatal; but without restraints, the fatal crash ratio is 1 in about 11. So the combined effect of lower restraint use and higher speed is a devastating combination that accounts for much of the high lethality of ID crashes.
- Number Injured (Including Fatalities) – Not only are ID crashes generally more severe to the driver, but the number of multiple injuries in these ID crashes is over-represented as well. This might have something to do with the preference of those going out to socialize to take some of their friends with them.
- Police Arrival Delay – ID crashes generally had longer police arrival delays; in this case all arrival delays over 31 minutes were over-represented. There can be little doubt that this has to do with the rural nature of these crashes and the potential that the late night occurrence might not be discovered for some time.
- EMS Arrival Delay – Higher EMS delays were over-represented for impaired driving injury crashes in all categories above ten minutes, and dramatically for the very longer times of 46 to 60 minutes and above. This obviously contributes to the severity of crashes and the chances that the crash results in one or more fatalities. As for the very long times, these might be due to the delay in discovering the crash as much as their generally over-represented rural locations.

- **Driver and Vehicle Demographics**
  - Driver Age – Younger (16-20 year old) drivers have a very serious problem in crash causation even in the absence of impairment. However, these crashes are not generally caused by ID up until ages 19 and 20, and even at these ages they are under-represented. At 23, the first age over-representation takes place and continues on to age 55. There is a bi-modal distribution in the 21-54 year olds; 21 through about 35, and a second group from 36 to 55. Generally, the first of these might be classified as largely social drinkers; while it is inescapable that the middle aged caused ID crashes would be largely problem drinkers.
  - Impaired Driver Gender –Males are a far greater issue in ID crashes, and if there are countermeasures that can be directed toward them, doing so would be much

more cost-effective than those that are not gender based, all other things being equal.

- Causal Vehicle Type – Pick-ups, which up had a significant over-representation and came out at the top of the Max Gain order because of their large number of ID involvements. Motorcycles were also highly over-represented. Also of interest is the proportion of pedestrians that involve ID, which is close to three times their expected number. ATVs had the highest over-representation (Odds Ratio = 4.580), perhaps because drivers do not believe that the ID laws apply to them as long as they are not on the public highways.
- Driver License Status – ID crashes are very highly over-represented in causal drivers without legitimate licenses challenging the effectiveness of license suspension and revocations as a traffic safety countermeasure, at least after the fact. There is no way to estimate its deterrent value.
- Driver Employment Status –ID driver unemployment rate at 37.38% is about 90% higher than expected. This factor will be watched carefully going forward.