MATH 599 Project:

Final Action Research Project

James Sheldon

University of Northern Colorado

MATH 599 Project:

Final Action Research Project

Description of Mathematical Problem

The initial problem that I started with was "is the world becoming a better place?" As I began to look at data and exploring what this question might mean, I found myself particularly intrigued by the questions of racial equality and looking at racial discrepancies in unemployment statistics. I decided to focus primarily on issues of race, which is not easily compared across countries, since each country defines its racial categorization system differently and collects different data. On the other hand, comparisons across State lines is more feasible given that there are national datasets available that are broken down by state.

The mathematical problem that I present here is a method to quantify the overall racial equality in the United States, by state, and across time. I present a method for deriving this number for each US state for the years 2010-2014, explore overall patterns in that number over time, and then make comparisons between this number and a number that quantifies the diversity in that state. Initial analyses are done using Microsoft Excel and final analyses for all 50 states are done with JMP scripting.

Initial Development of Measure

To simplify the initial process of developing my measures, I am going to start by comparing Arizona to California, since I lived in California for 34 years and Arizona for 3 years and have been heavily involved both in politics and in social science research in both places.

Based on my own experiences and understanding of legislative and demographic shifts in both states, my hypothesis is that California would have more racial equality in the 2010s than in the 1990s and that any given time would have more racial equality than Arizona. Specifically, I am going to compare 1991 to 2014, since the two data sets I have span different time frames, and that is the years that overlap for both data sets.

But, does political sentiment and legislative shifts coincide with more objective measures of quality of life for people of various racial groups? To answer this question, I explored two publicly available data sets, the Unemployment by State with Racial Cuts (Economic Policy Institute, 2017) and the FBI Uniform Crime Report Hate Crimes Statistics (FBI, 2018).

Unemployment

Unemployment is a key metric used by social scientists when attempting to assess the status of racial inequality. One traditional explanation for this problem is that white prospective workers have higher rates of education. (Emeka, 2018). However, studies show a high rate of discriminatory hiring practices even when workers have similar education levels. Emeka's approach was to explore the impact race adds when education is held constant and to explore how race can be used to predict unemployment. This approach makes sense when attempting to identify structural inequalities in employment. However, given that my goal is to quantify the overall status of racial inequality in a state rather than attempting to solve the problem of racialized unemployment, separating out education from unemployment is unnecessary for my analysis.

Unemployment figures have been in the news lately, given that the unemployment rate has been on the decline. There's an important caveat here, though; when unemployment is surveyed, the US Department of Labor only counts those who are completely unemployed, have actively looked for a job in the past four weeks, and who are currently available for work. (https://www.bls.gov/cps/cps_htgm.htm#unemployed). So, people who have stopped looking for work are not considered unemployed.

As I looked at the figures, I became interested in the differences between the unemployment rate for different racial groups; the US Department of Labor reports this by white, Black/African American, Asian, and Hispanic/Latino. There are considerable racial discrepancies in unemployment rates; for example, the white unemployment rate was 3.4% in Aug 2018 while the black unemployment rate was 6.3%. The Asian unemployment rate was 3.0% (although I would suspect there would be discrepancies if we broke this down by specific ethnicities rather than by just as Asian, which is unfortunately not routinely collected by the government) and the Hispanic/Latino unemployment rate was 4.7%.

The US Department of Labor does not have available for download that breaks down both state-by-state and by race. The Economic Policy Institute does, however, have state by state unemployment data available with the option of a racial breakdown. My goal in this step is to come up with a calculation to describe discrepancies between races; say, we have a white unemployment rate of 3.4% and a black unemployment rate of 6.3%, merely subtracting them to get 2.9% seems to be inadequate to describe the difference between them given that the black unemployment rate is almost twice (1.85x) the white unemployment rate. And, if we were to look at white, Black, and Hispanic rates, we need to combine all three into a number that reflects the closeness or distance from each other. In other words, our goal here is to meaningfully calculate the discrepancy between three numbers. Some initial factors that I considered were: can you compare percentages with each other? If so, is that a multiplicative rather than linear relationship? Looking ahead, I also wanted to think about how I might be able to compare the change over time between two states rather than just the change over time within an individual state.

Discrepancies Between Unemployment Percentages

The question I tackle in this section is developing a way to quantify discrepancies between percentages. Thinking about my hypothesis that we need to be using multiplicative reasoning, or geometric reasoning to understand the magnitude of the difference between the white unemployment of 3.4% and the black unemployment rate of 6.3%. I think I might want to invent here a geometric standard deviation to represent geometric rather than arithmetic relationships. (I imagine this already exists, but I am going to invent my own and then compare it to the standard method.) Thinking about how an arithmetic standard deviation measures the squares of the differences of the data points from the arithmetic mean, and then involves taking a single square root to account for the sum being in squared units, I am going to do something parallel for the geometric mean. Rather than taking the arithmetic difference of each data point from the arithmetic mean, I'm going to take the ratio of each data point from the geometric mean and I am going to multiply them, and then take the principal nth root of the resulting product.

Arizona Unemployment 2014 in %			
Races:			
Black	4.7		
White	5.5	Geometric Mean	5.98659
Hispanic	8.3	Geometric Standard Deviation	1

But, much like the idea of adding the sums of differences from the mean gives 0, multiplying the products of the differences from the geometric mean merely gives 1. What if we square the differences and take the 2th root?

Geometric Mean	5.98659
Geometric Standard Deviation	1

Sadly, that is still just 1. ☹

Thinking back about arithmetic standard deviation, where we multiplied a number by itself and then added those products, in a geometric standard deviation, maybe we need to raise the number to its own power and then multiply the products? And then maybe just take the nth root this time?

This yields:

Races:			
Black	4.7		
White	5.5	Geometric Mean	5.98659
Hispanic	8.3	Geometric Standard Deviation	1.063661

Is this any better than the arithmetic mean? The arithmetic mean was:

Arithmetic Mean	6.166667
Arithmetic Standard Deviation	1.890326

Which seems to better capture the discrepancies between these numbers.

What if we try to calculate the geometric standard deviation in yet another way? How about simply finding the ratios and then adding them and dividing by n? Let's try that:

Races:			
Black	4.7		
White	5.5	Geometric Mean	5.98659
Hispanic	8.3	Geometric Standard Deviation	1.03008

And it's even worse that way. Even though the Hispanic unemployment rate in Arizona in 2014 was twice that of the black unemployment rate, this method yields only 1.03.

Perhaps the issue here is that we've got one data point almost exactly at the geometric mean and there's only three data points, so we are kind of throwing off the measure of dispersion in some way? Perhaps we need to move beyond things being compared to a measure of center?

What if we ignore the relatively centered white unemployment and just compute the ratio of the highest data point, Hispanic unemployment to the lowest data point, black unemployment? Then we have

Hispanic to Black ratio	1.765957

Which seems much closer to what we were hoping for than any of these different forms of standard deviations!

More generally, I'm going to suggest here that we take three ratios, Hispanic to black, Hispanic to white, and white to black, or, if we put them in order $a < b < c$, then c/a, c/b, b/a, and then take the highest of the three ratios, since we're interested in the comparison that yields the maximum discrepancy, not in averaging out the three discrepancies. Which in this case is just the 1.766.

We will only ever have three data points using this EPI dataset, since it only breaks unemployment down into white, Hispanic, and black.

Perhaps multiplicative reasoning is not the right approach to this problem. An alternate idea to consider is to take sum of the absolute value of the differences between the data points, or in other words, if we to take | a-b| + |a-c| + |b-c|. Testing this on the Arizona data from 2014, we get a value of 2.4. Lets compare that to the California data for 2014:

California 2014 Unemployment by Race

		Absolute Value of	
Black	14	Differences	5.266667
Hispanic	8.5		
White	6.1		

So, a reasonable hypothesis here would be that California has much more of a problem with racial equality and unemployment than Arizona. On the other hand, this calculation is not accounting for the relative numbers of white, Hispanic, and Black people; California is 38.4% white, 38.6% Hispanic, and only 7% Black. I considered at this juncture throwing out a racial group from the calculation if the proportion in the population was less than a given percentage. On the other hand, I could weight the calculations based on the relative proportion in the population. This path makes more sense to me, because thinking of people in absolute terms, it seems to matter more that people are in poverty if there are more of them.

Let's use an example of a state with a much higher percentage of Black people. For example, California is 7% black, so there's 270,045 Black people in California, and 14% of them are unemployed, so that's 37,806 Black people unemployed. By contrast, Georgia is 32.4% Black, which is 3,271,240 people, and 12.5% of them are unemployed, so that's 408,905 Black people unemployed. So it seems reasonable that it is objectively more of a problem to have a racial disparity in unemployment when a greater percentage of people of that race are unemployed.

Let's try to find a way to weight these figures. Let's take California's 6.1% White unemployment with 38.4% white population, 8.5% Hispanic unemployment with 38.6% Hispanic population, and 14% Black unemployment with 7% Black population. What I am going to propose here is to create a number that's about the overall impact of unemployment on a population, or unemployment % per population %.

California 2014 unemployment

	Unemployment %	Population %	Ratio
Black	14	7	2
White	6.1	38.4	0.158854
Hispanic	8.5	38.6	0.220207

Now, let's use the absolute value method to find the sum of the differences. |2-0.158854| + |0.158854-0.220207| + |2-0.220207|. This gives us a value of 3.682292.

Let's try this for Arizona:

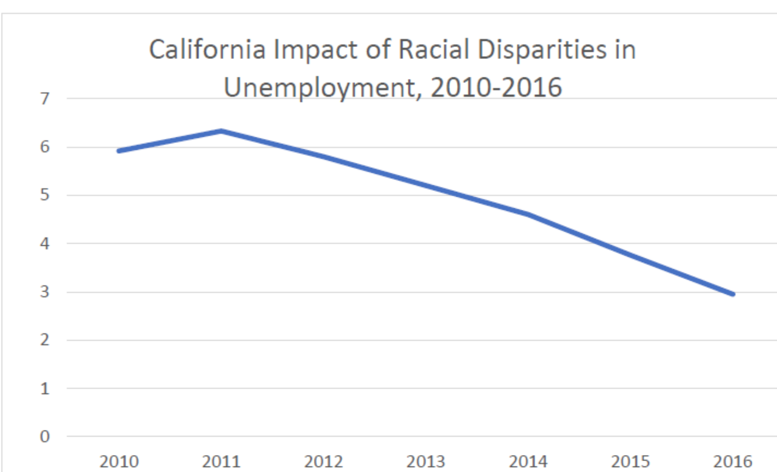
Arizona 2014 unemployment

	Unemployment %	Population %	Ratio
Black	4.7	4	1.175
White	5.5	56.1	0.098039
Hispanic	8.3	30.5	0.272131
			2.153922

This method produced very unexpected results, with the Arizona measure in particular being widely divergent from year to year. Here is the results of this first method:

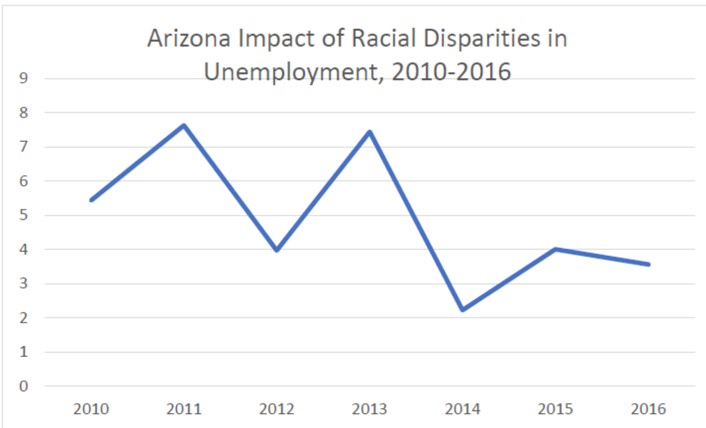
California Unemployment 2011-2016	Unemployment 1994-2016					
	Population % 2010	Unemployment % 2010	Pop 2011	UN 2011	Pop 2012	UN 2012
Black	5.9	18.9	5.8	19.7	5.8	18
White	41.2	10	40.7	9.5	40.1	8.1
Hispanic	36.7	14.7	37.2	13.8	37.6	12.7
	Ratio B	3.203389831		3.39655		3.10345
	Ratio W	0.242718447		0.23342		0.202
	Ratio H	0.400544959		0.37097		0.33777
		5.921342768		6.32627		5.80291

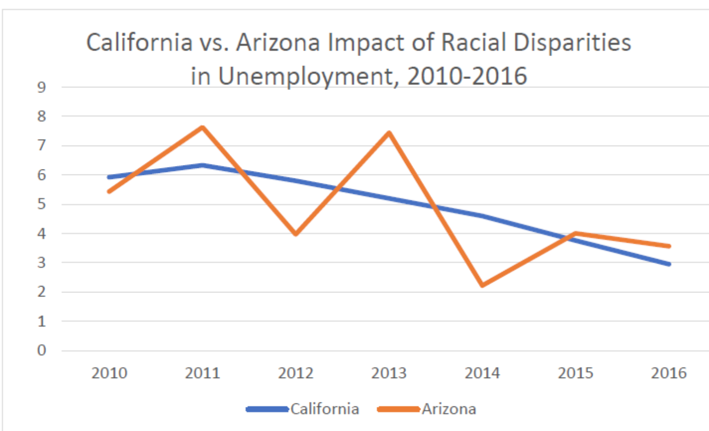
Pop 2013	UN 2013	Pop 2014	UN 2014	Pop 2015	UN 2015	Pop 2016	Un 2016
5.7	15.9	5.7	14	5.6	11.2	5.6	8.9
39.7	7.4	39.2	6.1	38.7	4.7	38.4	4.4
37.9	10.2	38.2	8.5	38.4	7.5	32.1	6.6
	2.78947		2.45614		2		1.589286
	0.1864		0.155612		0.121447		0.114583
	0.26913		0.222513		0.195313		0.205607
	5.20615		4.601056		3.757106		2.949405



Arizona

2010	5.43
2011	7.63
2012	3.97
2013	7.44
2014	2.22
2015	4
2016	3.56





Given the widely divergent graph for Arizona, at this point, I consulted my professor, who observed that I had done the calculation backwards, given that with unemployment % per population percentage, the impact of the unemployment would go DOWN as the population percentage went up. He suggested instead using unemployment times population percentage.

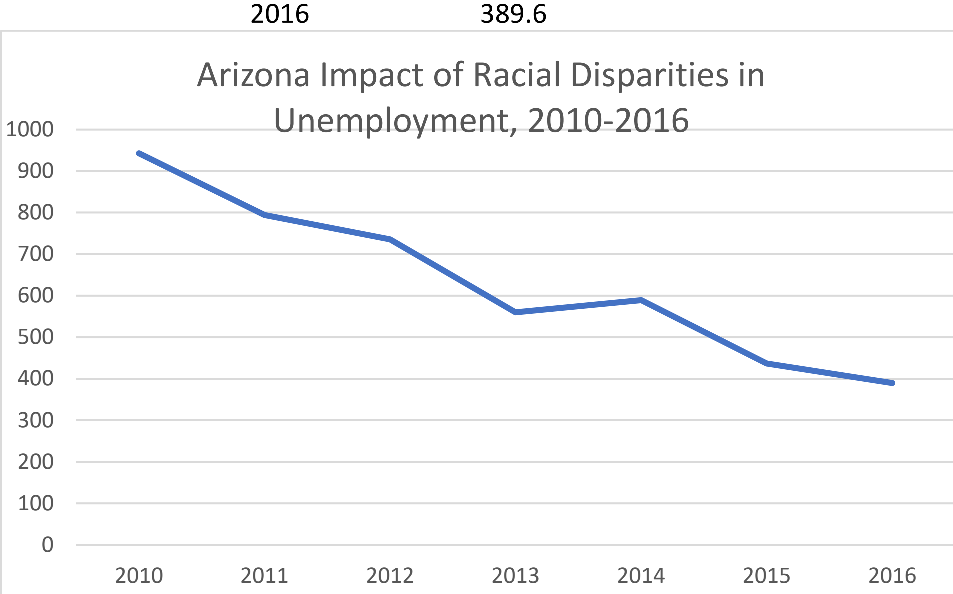
Fixing the measure to account for this, I next computed the statistic for 2010-2016. I did not use the unemployment values from 1991-2009 because I did not have access to the corresponding racial population percentages on a state by state basis for that time period.

Arizona	Unemployment 2010-2016					
	Population % 2010	Unemployment % 2010	Pop 2011	UN 2011	Pop 2012	UN 2012
Black	3.7	10.6	3.8	15	3.8	8
White	58.7	8.7	58.2	7.8	57.7	6.9
Hispanic	29	13.4	29.4	12.7	29.7	10.5
	B	39.22		57		30.4

W	510.69	453.96	398.13
H	388.6	373.38	311.85
	942.94	793.92	735.46

Pop 2013	UN 2013	Pop 2014	UN 2014	Pop 2015	UN 2015	Pop 2016	Un 2016
3.9	14.9	3.9	4.7	4	8.3	4	7.4
57.3	5.9	56.9	5.5	56.5	4.2	56.1	4
29.9	9.4	30.1	8.3	30.3	8.3	30.5	7.1
	58.11		18.33		33.2		29.6
	338.07		312.95		237.3		224.4
	281.06		249.83		251.49		216.55
	559.92		589.24		436.58		389.6

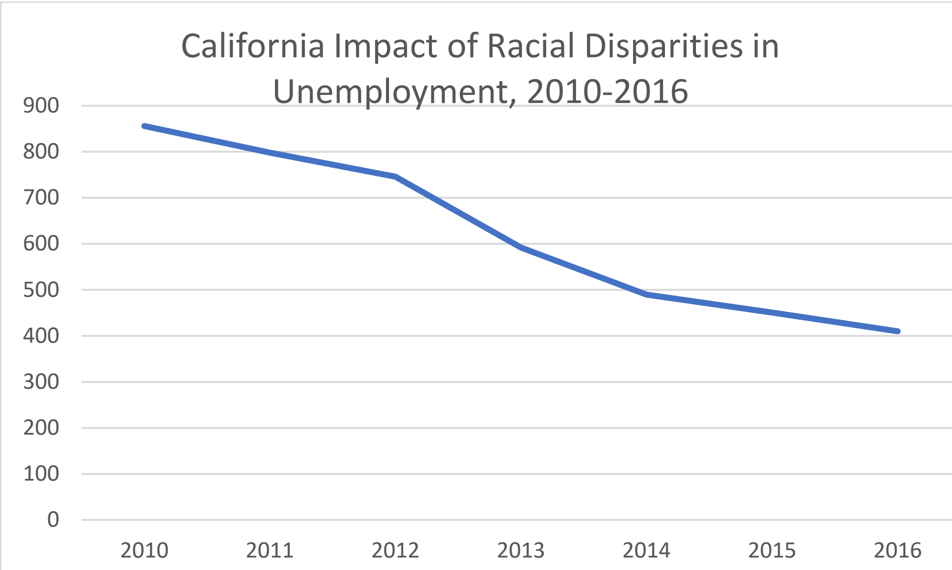
2010	942.94
2011	793.92
2012	735.46
2013	559.92
2014	589.24
2015	436.58
2016	389.6

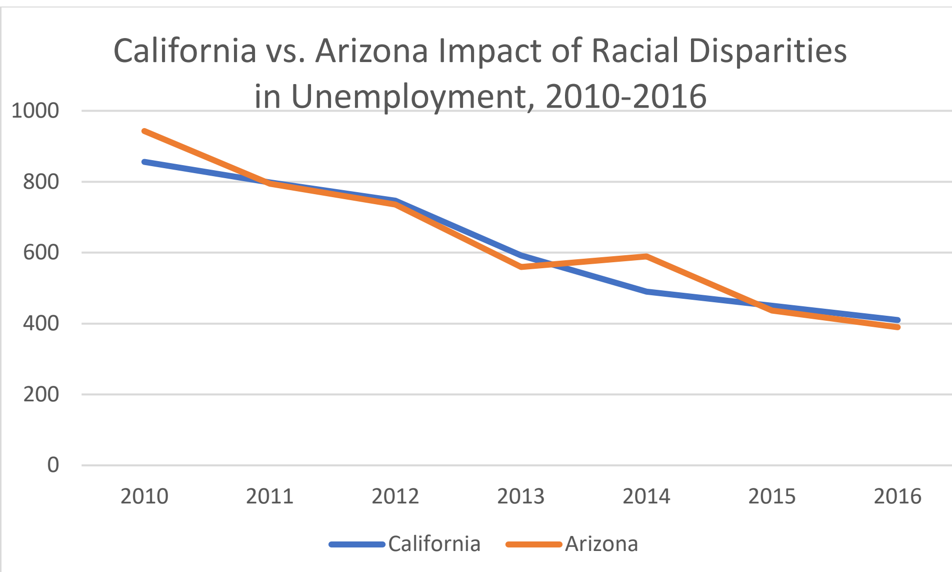


And for California:

2010	855.96
2011	798.2
2012	746.24
2013	591.9
2014	489.8
2015	450.56

2016	409.84





There was an additional problem observed by the instructor with this new method, which can be seen when we look at the Arizona data:

Arizona	Unemployment 2010-2016					
	Population % 2010	Unemployment % 2010	Pop 2011	UN 2011	Pop 2012	UN 2012
Black	3.7	10.6	3.8	15	3.8	8
White	58.7	8.7	58.2	7.8	57.7	6.9
Hispanic	29	13.4	29.4	12.7	29.7	10.5
	B	39.22		57		30.4
	W	510.69		453.96		398.13
	H	388.6		373.38		311.85
		942.94		793.92		735.46

From 2010 to 2011, the unemployment impact figure for blacks went from 39.22 to 57, while the unemployment impact figure (population % times unemployment percentage) for whites went from 510.69 to 453.96. Because there are so many more white people than black people in Tucson, the white figure vastly exceeds the black figure, and so when black unemployment rises and white unemployment falls, paradoxically it closes the gap between the two figures with this method, and so even though the racial disparity has gotten worse this method shows it as having gotten better.

The new version of the measure does not use the population %. The revised figures are:

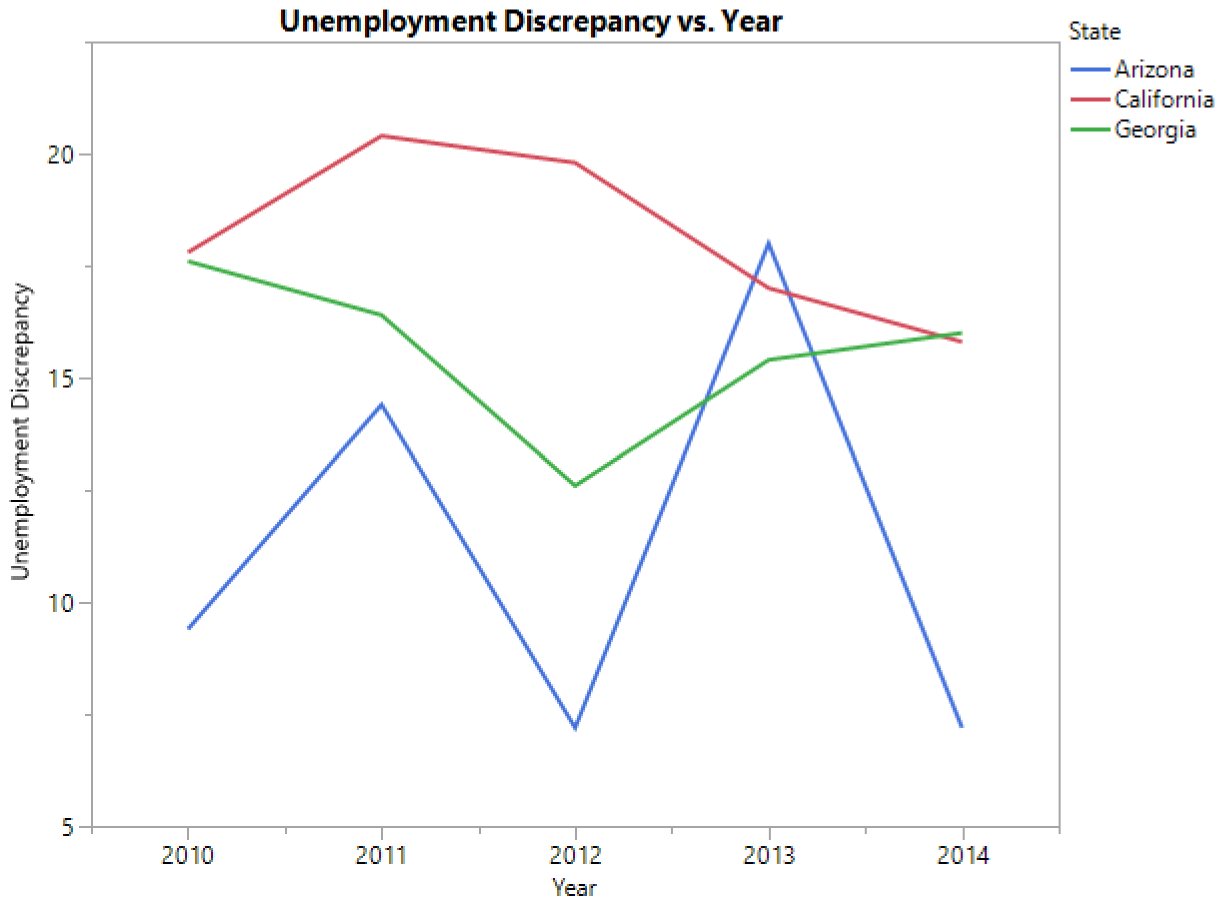
2010 Discrepancy	2011 Discrepancy	2012 Discrepancy	2013 Discrepancy	2014 Discrepancy
9.4	14.4	7.2	18	7.2

Which better reflects what happened in 2011, where the gap between white and black unemployment increased.

The final version of these figures was calculated using JMP scripting:

```
UnemploymentDiscrepancy = abs(BlackUnemployment - HispanicUnemployment) +
      abs(BlackUnemployment - WhiteUnemployment) +
      abs(HispanicUnemployment - WhiteUnemployment);
```

	State	Year	Unemployment Discrepancy
11	Arizona	2010	9.4
12	Arizona	2011	14.4
13	Arizona	2012	7.2
14	Arizona	2013	18
15	Arizona	2014	7.2
21	California	2010	17.8
22	California	2011	20.4
23	California	2012	19.8
24	California	2013	17
25	California	2014	15.8
51	Georgia	2010	17.6
52	Georgia	2011	16.4
53	Georgia	2012	12.6
54	Georgia	2013	15.4
55	Georgia	2014	16



Hate Crimes Reporting

In addition to more structural inequality such as unemployment, I also decided to examine reported hate crimes. The FBI defines a hate crime as being "motivated in whole, or in part, by an offender's bias against the victim's perceived race, gender, gender identity, religion, disability, sexual orientation, or ethnicity." And provides data from 1991-2014, broken down by state and by Anti-American Indian, Anti-Asian, Anti-Bisexual, Anti-Black, Anti-Catholic, Anti-Female, Anti-Gay, Anti-Gender Nonconforming, Anti-Heterosexual, Anti-Hispanic or Latino, Anti-Mental Disability, Anti-Muslim, Anti-Not Hispanic or Latino, Anti-Jewish, Anti-Lesbian, Anti-LGBT, Anti-Multi Racial, Anti-Multi Religious, Anti-Physical Disability, Anti-Protestant, and Anti-White. To align with the unemployment data, I'm going to look at Anti-Black, Anti-Hispanic/Latino, and Anti-White.

As an example of this data, in 2014 in Arizona, there were 93 Anti-Black incidents, 26 Anti-Hispanic/Latino Incidents, and 15 Anti-White Incidents. One thing that makes this data complicated to interpret is that incidents can fall into up to 4 categories, so these are not necessarily discrete incidents. Another complexity is that there might be more of a given racial group in a state, and that it is not entirely clear how many people there are of each racial group. For example, in 2010, 83.1% of Arizona was white, but 31.4% was Hispanic/Latino, because an individual can be both White and Hispanic (for example, if the individual is of Spanish ethnicity). So we would break it down into White, not Hispanic/Latino, 54.9% and Hispanic/Latino, 31.4%. Asian is 3.5% and and Black is 5.0%. (https://www.census.gov/quickfacts/fact/table/az,US/RHI125217) So it seems like the 93 Anti-Black incidents is particularly noteworthy given that the Black population in Arizona is only 5%. So it seems like we would want to adjust these hate crime statistics to account for the relative percentage of the population before we tried to compare them.

So let's say we divide these figures by the percentage of the population for that racial group. Let's assume Anti-White Incidents relate only to White, Non-Hispanic/Latino folks, as a simplifying assumption. The adjusted figures would be 93/.05 = 1860 Anti-Black, 26 / .314 = 82 Anti-Hispanic/Latino, and 15 / .549 = 27 Anti-White. The reason why this method works is that it is calculating based on if that particular racial group was 100% of the population. For example, for the 93 anti-black incidents and 5% of the population being black, 93 / .05 is the same as 93 * (1/.05) = 93 * 20 = 1860. It is multiplied by 20 since there are 20 5%s in 100%.

	Arizona		
	2014 Incidents (Anti-)	2010 Proportion of Race	Adjusted Incidents
White	15	0.549	27.32
Hispanic/Latino	26	0.314	82.80
Black	93	0.05	1860.00

	California		
White	28	0.372	75.27
Hispanic/Latin	60	0.391	153.45
Black	243	0.065	3738.46

Although I considered both standard deviation and the sum of distances approach, I took a close look at the data and realized that the hate crime reporting systems must differ considerably from state to state, as Georgia in 2010 had 8 Anti-Black hate crimes, 1 anti-Hispanic hate crime, and 2 Anti-White Hate Crimes, while California in 2010 had 323 Anti-Black hate crimes, 119 Anti-Hispanic hate crimes, and 47 Anti-White Hate Crimes. In order to better reflect the differences in reporting between states, I altered my measure to take the geometric mean of the three ratios of the adjusted hate crime values, or in other words, for Georgia in 2010: ((8/1)(8/2)(1/2)) ^ (1/3) = 1.14399002 and for California in 2010: 12.5051863. The following is the JMP script for the final version of the measure:

```
BlackAdjusted = BlackHateCrimes / BlackPopulationPercentage +1;
HispanicAdjusted = HispanicHateCrimes / HispanicPopulationPercentage +1;
WhiteAdjusted = WhiteHateCrimes/WhitePopulationPercentage + 1;

HateCrimeDiscrepancy = ((BlackAdjusted/HispanicAdjusted)*
       (HispanicAdjusted/WhiteAdjusted)*
       (BlackAdjusted/WhiteAdjusted))^(1/3);
```

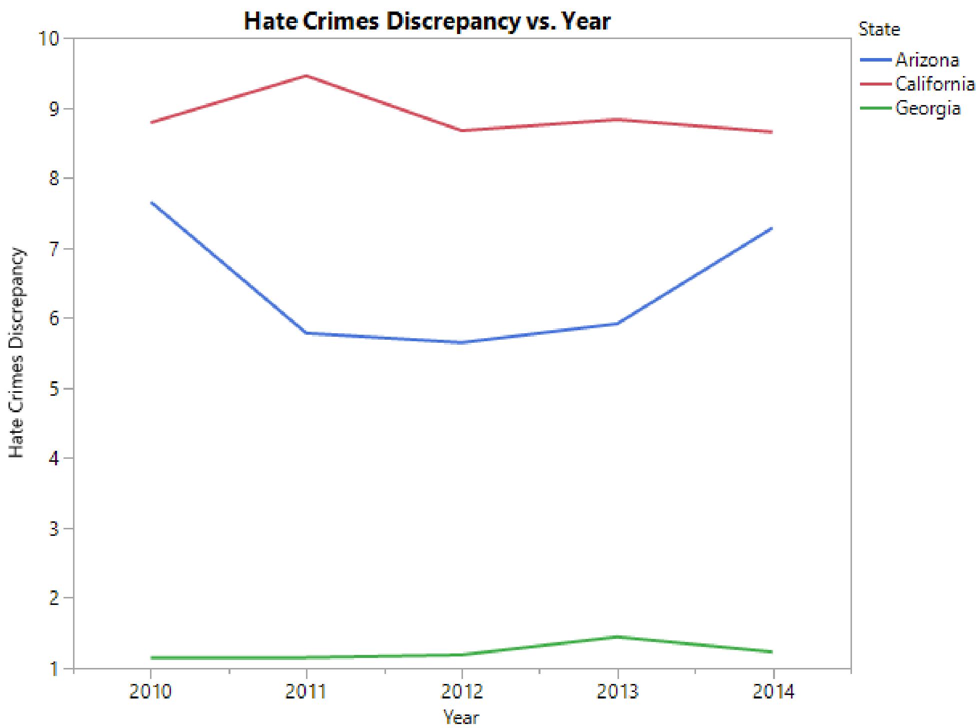
Demonstrating this method on Arizona, California, and Georgia, we have:

	State	Year	Race	Hate Crimes	% of Population
1	Arizona	2010	Black	84	3.7
2	Arizona	2010	Hispanic	25	29
3	Arizona	2010	White	7	58.7
4	Arizona	2011	Black	59	3.8
5	Arizona	2011	Hispanic	34	29.4
6	Arizona	2011	White	11	58.2
7	Arizona	2012	Black	56	3.8
8	Arizona	2012	Hispanic	25	29.7
9	Arizona	2012	White	10	57.7
10	Arizona	2013	Black	61	3.9
11	Arizona	2013	Hispanic	17	29.9

12	Arizona	2013	White	9	57.3
13	Arizona	2014	Black	93	3.9
14	Arizona	2014	Hispanic	26	30.1
15	Arizona	2014	White	15	56.9
16	California	2010	Black	323	5.9
17	California	2010	Hispanic	119	36.7
18	California	2010	White	47	41.2
19	California	2011	Black	312	5.8
20	California	2011	Hispanic	88	37.2
21	California	2011	White	36	40.7
22	California	2012	Black	290	5.8
23	California	2012	Hispanic	88	37.6
24	California	2012	White	40	40.1
25	California	2013	Black	287	5.7
26	California	2013	Hispanic	64	37.9
27	California	2013	White	38	39.7
28	California	2014	Black	243	5.7
29	California	2014	Hispanic	60	38.2
30	California	2014	White	28	39.2
31	Georgia	2010	Black	8	30
32	Georgia	2010	Hispanic	1	8.3
33	Georgia	2010	White	2	56.8
34	Georgia	2011	Black	9	30.1
35	Georgia	2011	Hispanic	0	8.6
36	Georgia	2011	White	3	56.3
37	Georgia	2012	Black	11	30.2
38	Georgia	2012	Hispanic	0	8.8
39	Georgia	2012	White	3	55.8
40	Georgia	2013	Black	28	30.3
41	Georgia	2013	Hispanic	0	8.9
42	Georgia	2013	White	6	55.4
43	Georgia	2014	Black	14	30.4
44	Georgia	2014	Hispanic	3	9.1
	State	Year	Race	Hate Crimes	% of Population
45	Georgia	2014	White	4	55

	State	Year	Unemployment Discrepancy	Hate Crime Discrepancy
11	Arizona	2010	9.4	7.65444548
12	Arizona	2011	14.4	5.7808978
13	Arizona	2012	7.2	5.64507636
14	Arizona	2013	18	5.91399277
15	Arizona	2014	7.2	7.28498
21	California	2010	17.8	8.7853755
22	California	2011	20.4	9.45547382
23	California	2012	19.8	8.67071055
24	California	2013	17	8.82967875
25	California	2014	15.8	8.65257055
51	Georgia	2010	17.6	1.14399002
52	Georgia	2011	16.4	1.15003037
53	Georgia	2012	12.6	1.18785865
54	Georgia	2013	15.4	1.44448004
55	Georgia	2014	16	1.22841952

And here is the Hate Crimes discrepancy measure for the three states:



Bringing the Two Measures Together

There are several different options for us to consider as we seek to combine these two measures. One is to weight them in some fashion, based on the relative importance. It seems like more of a value judgement, though, whether being safe to walk down the street is more important than having a job and what the relative importance of each would be. So rather than weighting them, I am going to take an average. I have two choices to consider; one being the arithmetic mean and one being the geometric mean. In this analysis, I chose the geometric mean because it is less affected by the two factors being on a different scale and having different relative magnitudes. I considered scaling them down onto the same scale, but given that the maximum value for each does not seem particularly meaningful (merely representing the data points being as far from each other as possible), I chose to take the geometric mean instead. To do this, I used the following JMP script:

```
tableOutput:Combined Discrepancy[OutputRow] =
(HateCrimeDiscrepancy*UnemploymentDiscrepancy)^(1/2);
```

Here's the results for Arizona, California, and Georgia:

	State	Year	Unemployment Discrepancy	Hate Crime Discrepancy	Combined Discrepancy
11	Arizona	2010	9.4	7.65444548	8.48243995
12	Arizona	2011	14.4	5.7808978	9.12386586
13	Arizona	2012	7.2	5.64507636	6.37530782
14	Arizona	2013	18	5.91399277	10.3175515
15	Arizona	2014	7.2	7.28498	7.24236536
21	California	2010	17.8	8.7853755	12.5051863
22	California	2011	20.4	9.45547382	13.8885444
23	California	2012	19.8	8.67071055	13.1026741
24	California	2013	17	8.82967875	12.2517158
25	California	2014	15.8	8.65257055	11.6923314
51	Georgia	2010	17.6	1.14399002	4.48711759
52	Georgia	2011	16.4	1.15003037	4.34286749
53	Georgia	2012	12.6	1.18785865	3.86872317
54	Georgia	2013	15.4	1.44448004	4.71645976
55	Georgia	2014	16	1.22841952	4.43336355

Population Diversity Measure

In order to consider population diversity, I used a method from Simpson (1949) for measuring categorical diversity which involves finding the proportions each category is from the total, squaring them, then summing then, and then subtracting from 1. If we have a perfect split between the three categories of 33%, 33%, and 33%, this measure yields a .6733. So Teachman (1980) suggests multiplying by the number of categories over the number of categories minus 1, which gives (3/2)(.6733) = approximately 1. This is the method which I used to measure population diversity.

Here's the JMP script for this method:

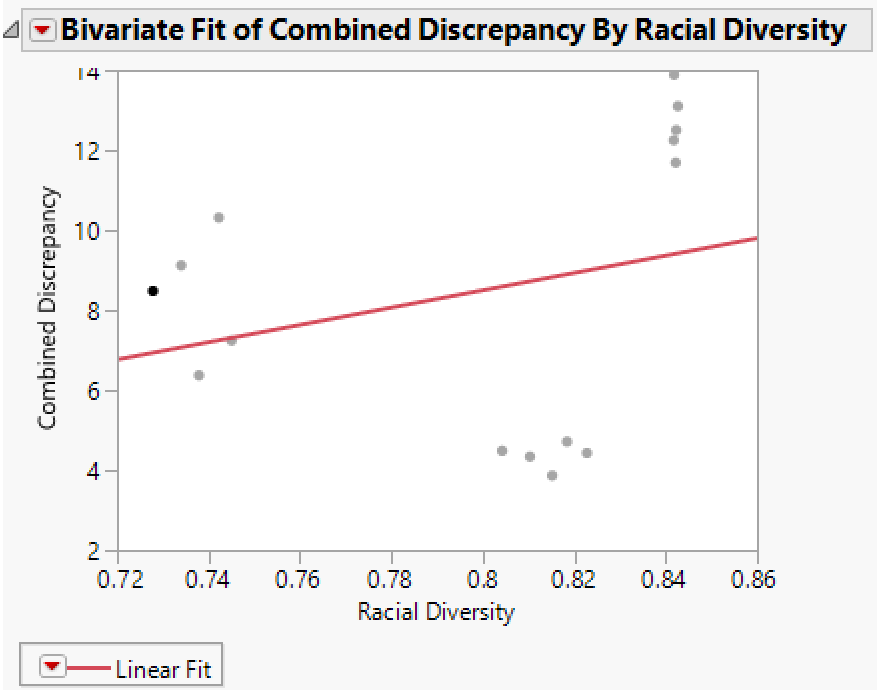
```
tableOutput:RacialDiversity[OutputRow] = (3/2)*(1 -
((BlackPopulationPercentage/ThreePopulationPercentage)^2 +

(HispanicPopulationPercentage/ThreePopulationPercentage)^2 +

(WhitePopulationPercentage/ThreePopulationPercentage)^2));
```

And the resulting table:

	State	Year	Combined Discrepancy	Racial Diversity
11	Arizona	2010	8.48243995	0.72784284
12	Arizona	2011	9.12386586	0.73400878
13	Arizona	2012	6.37530782	0.73789892
14	Arizona	2013	10.3175515	0.74224535
15	Arizona	2014	7.24236536	0.74502137
21	California	2010	12.5051863	0.84229271

22	California	2011	13.8885444	0.84182714
23	California	2012	13.1026741	0.84266342
24	California	2013	12.2517158	0.84175567
25	California	2014	11.6923314	0.84219352
51	Georgia	2010	4.48711759	0.80421406
52	Georgia	2011	4.34286749	0.81030582
53	Georgia	2012	3.86872317	0.8151605
54	Georgia	2013	4.71645976	0.81840642
55	Georgia	2014	4.43336355	0.82275636

In order to assess whether combined discrepancy was correlated with racial diversity, I did a linear regression. My hypothesis was that there would be a linear relationship between racial diversity and my measure of combined discrepancy. Here, this is shown for Arizona, California, and Georgia, and we can see that there is no linear relationship:



Linear Fit

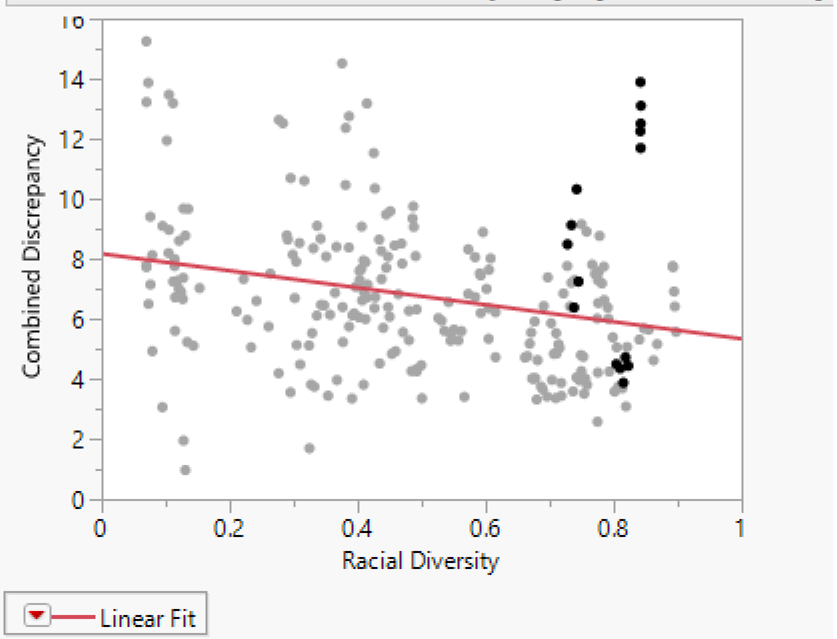
Combined Discrepancy = -8.817141 + 21.647293*Racial Diversity

Summary of Fit

RSquare	0.075096
RSquare Adj	0.003949
Root Mean Square Error	3.637502
Mean of Response	8.455368
Observations (or Sum Wgts)	15

In order to test whether there was a linear relationship between all the states, I computed the combined discrepancy and racial diversity measure for all 50 states (DC was included, Hawaii was excluded). Here was the linear regression for all 50 states:

Bivariate Fit of Combined Discrepancy By Racial Diversity



Linear Fit

Combined Discrepancy = 8.1692441 - 2.8355958*Racial Diversity

Summary of Fit

RSquare	0.071584
RSquare Adj	0.067841
Root Mean Square Error	2.446048
Mean of Response	6.749852
Observations (or Sum Wgts)	250

And the r^2 of 0.07 does not lend confidence to there being any linear relationship between racial diversity and combined discrepancy.

Further investigation might explore other factors that influence racial equality, such as what I address in my teaching innovation, average income and proximity to pollution. In the teaching innovation, I break average income by race and proximity to pollution down by race on the zip code level, which using my methods (essentially, manually entering data into JMP from various spreadsheets), would not be a practical method of analysis. One solution to this might be to write JMP script code to parse the actual spreadsheets that come from each of these data sources, instead of entering the data by hand so it is in the proper places in my JMP tables.

Further investigation into racial diversity measures might take into account the specific histories of different racial groups in different areas instead of making the assumption that the three races under consideration should each be at 33% in each state.

Teaching Innovation

Description of Class

The class which I'm teaching is a 3-unit, college credit-bearing class for non-STEM majors called "Topics in College Mathematics". At our school, after completing a beginning algebra class, there are three tracks. The first path , for STEM majors, involves taking intermediate algebra, precalculus, and then calculus. The second is more intended for majors that need some math but aren't as math intensive, and students take intermediate algebra, college algebra, and then either statistics or brief calculus. The final path is to move from beginning algebra into the class that I teach, Topics in College Mathematics.

This course begins with arithmetic and geometric sequences, then moves into linear and exponential growth. Exponential growth is then used to teach compound interest and loan formulas. The next section of the class involves statistics and data analysis; first, the course covers how to define a population, how to conduct a survey, and how to set up an experiment. Then the course moves into covering how to present data using charts and graphs and how to calculate simple statistics such as measures of center and measures of spread. Next, students are given a basic introduction on how to do linear regression and how to work with a normal distribution. Finally, the course ends with students working with simple applications of probability.

Background for Teaching Innovation

There are two goals that I sought to build into my teaching innovation; both bringing into the classroom discussions of racial equity, which arise naturally out of my mathematical research, and incorporating more use of computer technology in a class which I have traditionally taught using only scientific calculators.

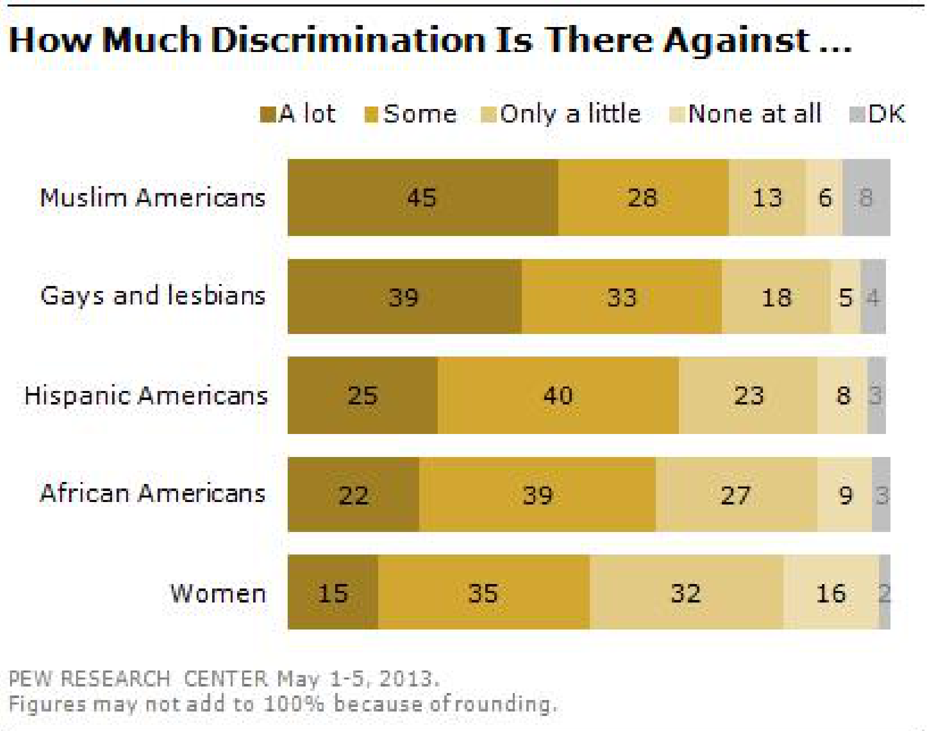
Questions of social justice and equity are at the forefront of the field of mathematics education. For example, the National Council of Supervisors of Mathematics and TODOS: Mathematics for All recently released a statement titled Mathematics Education Through the Lens of Social Justice, which amongst its many action items proposed that teachers should "Include tasks that demand quantitative analysis of fairness and civic engagement issues" (2016, p.5).

The class that I teach only requires a scientific calculator and does not utilize graphing calculators, although students are allowed to use them on exams if they so choose (I usually have 1-2 students who use a graphing calculator). Some colleagues of mine at faculty meetings have mentioned that they have students work with Google Sheets, and so I was interested in exploring how to incorporate that into the classroom. Our school has a laptop cart of 20 laptops available for teachers to reserve for classroom use.

Setting the Stage for the Teaching Innovation: Preliminary Lesson 1

Leading up to my teaching innovation lesson, I incorporated discussions of racial equity into two previous lessons, the first being a lesson on how to critically analyze visual representations of data (something that students will be required to do both in an independent project and on the final exam) and the second being a lesson about measures of center (mean and median).

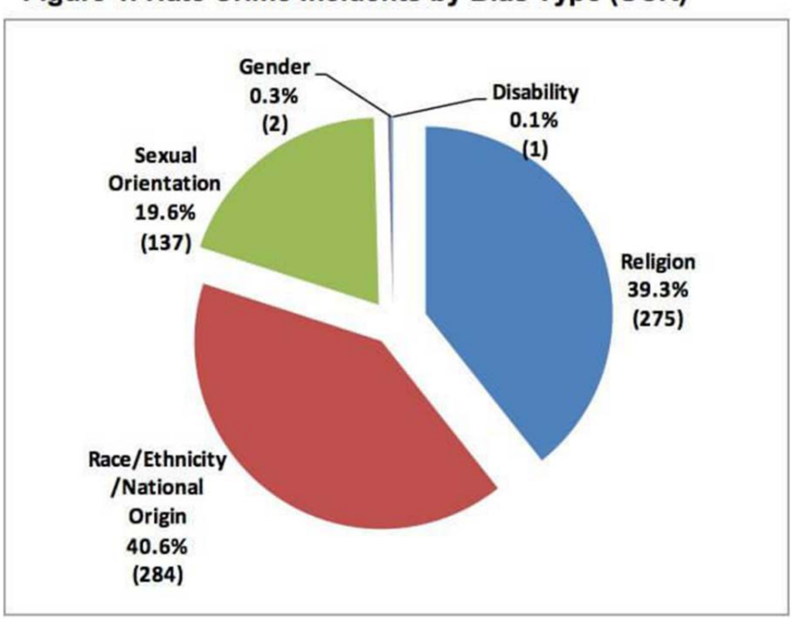
In the first lesson, students analyzed the following three graphs.



Graph 1 (Pew Research Center, 2013)

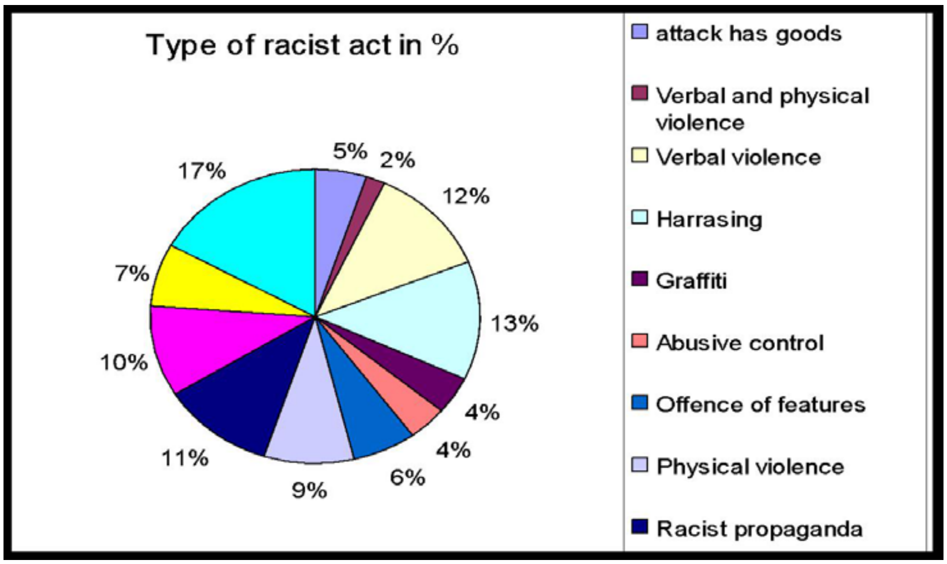
One the first graph, discussion centered around the question of why a disparate set of categories was being compared, such as a religion, a sexual orientation, an ethnicity, a race, and a gender. Students also raised questions about why the total number of people is not included on the graph and that it does not tell the breakdown of who took the survey, nor do they disaggregate who claimed what. Students also found the stacked bar graph misleading, as it was hard to follow what was in which categories, and many students felt like there was a lack of emphasis as to what the creator wanted you to see.

Figure 1. Hate Crime Incidents by Bias Type (UCR)



Graph 2 (Facts.net, 2014)

On the second graph, discussion initially focused on the lack of a date on this chart and the lack of information about the location of the crime incidents. (I filled in some context and let students know that UCR stands for the federal FBI uniform crime report.) Students were concerned that this graph gives the impression that each crime falls into only one category, when (as my research showed) a crime can actually be reported in up to 4 categories at a time. Some students also pointed out that if we included sexual assaults that had gender as part of their motivation, there would be far more than 2 gender-based hate crimes reported, and so we had a brief discussion as to whether all sexual assaults were gender-based.



Graph 3 (Source unknown)

With this graph, discussion centered around a number of things; the graph does not say where or when the racist acts happened, there is no data source identified, the colors on the labels are too similar to be able to tell them apart, and moreover, there are more colors on the graph than there are on the labels.

Setting the Stage for the Teaching Innovation: Preliminary Lesson 2

Lesson 2 covered mean and median. As a trial run of the idea of using real world data on spreadsheets, I used Census data and gathered data on median and mean incomes in each zip code in Tucson and asked students to calculate the median of the data manually by sorting the data. I then showed them the actual median for the area and asked them to think about why it might be different from what we calculated. Some students suggested that perhaps we were missing some zip codes (there are obvious gaps between zip codes). I explained to them that the gaps between zip codes are due to zip codes reserved for PO Boxes, which don't have anyone living in them. After giving them some time to ponder things, I asked them to look at the populations of each zip code, and they quickly noticed each zip code had different numbers of people. I talked about how we can compute a weighted median to account for this. At this point, things went rather awry, there became vocal pushback from a few of the more mathematically astute but sometimes stubborn students in my class, and then one by one they understood and tried to explain it to their classmates. It turns out we spent so much time deciding if we could compute weighted medians that we never actually even computed it!

Several students after class said they felt like it would have been better to learn things like weighted medians on simpler, single-digit data before trying to apply it to real world data, which was kind of disheartening given that the whole point of this innovation is about real world data.

Preparing for the Teaching Innovation

Day one started with the question of correlation; we have already talked about experiments and descriptive studies, and so I posed the two questions I have for the unit: is there a relationship between income and race, and is there a relationship between race and environmental justice (in other words, do people of color live near more pollution than white people)? I asked students to think-pair-share to discuss what their conjectures about these would be and how they think we might be able to test it. I used this as a formative assessment to check their understanding of previous material on descriptive vs experimental studies, too, by asking whether their ideas are descriptive or experimental.

We also talked about racial categories and different ways we might calculate things, such as percentage of white and white to Hispanic ratio. (The only other significantly large racial group here is Tucson is Hispanic people). White to non-white ratio comes from Downey's (1998) research on environmental justice, but percentage of non-white is relatively equivalent.

I prepared two "cleaned" data sets that has Tucson, AZ (where I teach) Zip Codes. Data set A has the % of white, non-hispanic people, the ratio of white to Hispanic people, the total population, and the median and mean incomes of each zip code. Data Set B has the same data about race ratio, %, and total population, and then the EPA pollution TRI data for total pollution emissions for that zip code.

We did this as a whole class activity with students in groups of two to three around each laptop. We had already done some basic spreadsheet skills in the previous lesson, so hopefully that will go smoother. Some students had trouble with the trackpads in the last class, so I secured a box of mice to go with the laptops.

I started with a short lecture about correlation coefficient, explaining what a positive and negative correlation coefficient is and then demonstrating how to find one in Google Sheets using a dataset from the class textbook that has an almost perfect correlation:

Example 1 Table 1. Sample of five children's ages and number of words in the vocabulary.

x, age in months	12	13	16	16	18
y, number of words in vocabulary	5	9	18	22	31

(Table used with permission).

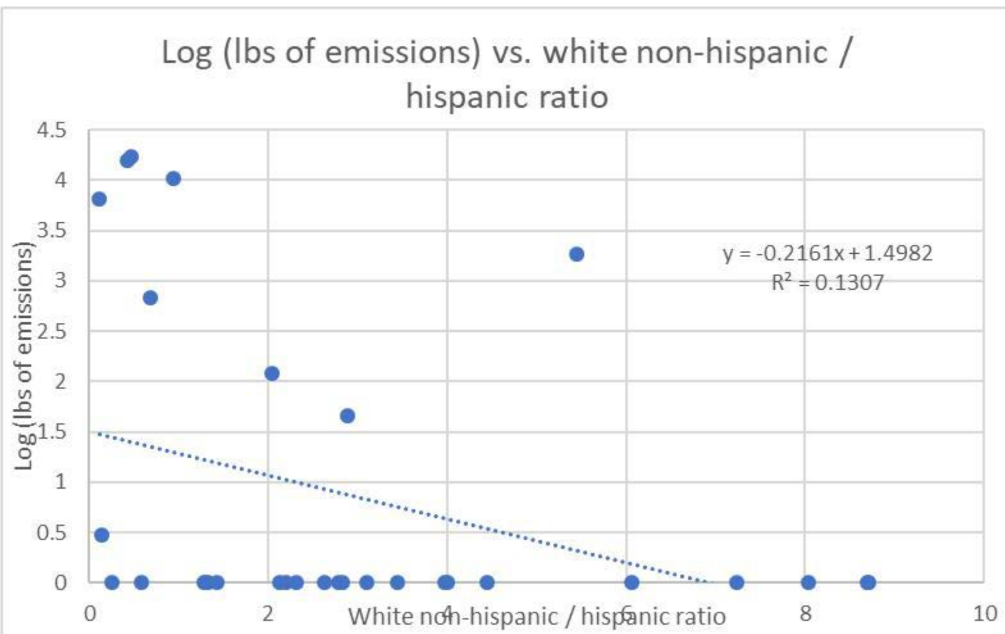
I then introduced the goal of figuring out the relationship between race and income and explain how we are going to do it. I distributed a worksheet to guide students, that lays out each step and tells them where to pause and check in with the instructor.

In the first step, invited each group to decide whether they want to use % of white, non-hispanic people or white to Hispanic ratio, and then to plot the line using the spreadsheet with Data Set A. (From prior experimentation, I know this line will have a r^2 of about 0.5).

Rather than immediately tell them how to do a linear regression, I invited them to consider where they think the best-fit line would be (using a drawing tool to draw their own line) and ask them to consider how they would know if that's the best fit line, or in other words how one would come up with it in a rigorous and precise manner. Then brought the whole class back together to discuss their ideas.

I then had students do the regression with the tools and compare it to their line, and discuss what the r^2 = 0.50 actually means, whether that means there is a relationship or not and how you might be able to decide.

In the second class, I had them attempt as similar method with Data Set B, which from my own experimentation shows a very weak (r^2 = 0.10) relationship. This is due, though, to there being significant zip codes with no pollution, and so even though almost all the polluted places have mostly non-white people in them, there are a lot of non-white people who do not live near pollution. So the graph ends up having clusters:



Making it difficult to actually fit a line. Downey (1998) though actually used pretty small r^2 values as evidence by doing multiple regression and comparing it to other factors, such as income, so I discussed with my students about how a low r^2 doesn't always mean no relationship and that looking at the graph is essential to be able to interpret r values. Likewise, it is common when doing mathematics for social justice to consider there to be a relationship even when r^2 is relatively low; McCoy (2008) did a high school lesson about poverty in which r^2 was 0.35. I concluded by opining about how there are many different tools and that an important part of statistics is being flexible and knowing how to choose a tool for a particular task and the limitations that your tool has.

Final Summative Project

My unit on descriptive and inferential statistics through racial justice closed with a project used as a summative assessment (See Appendix E for full project description as was handed out to students). In this project, students are asked to choose a social problem of their own. First, they consult four sources to find two graphs, one which they consider particularly effective and one which they consider particularly ineffective. Using provided guidelines, they wrote a critique of these graphs. Second, made a list of at least three variables that they might collect data about to research their chosen problem. They described a method of data collection, identify whether the variables are categorical or quantitative, and hypothesize about the possible relationship between the variables. Using a guide for evaluating credible sources, they found one credible source that explores two of these variables, and compare it to their own hypothesis. Finally, they discussed how this helps them better understand their two graphs.

I'm going to present one example of a student's work on this final project, and analyze their performance on this closing project. This student chose to focus on school standards and assessment, and critiqued the following graph:

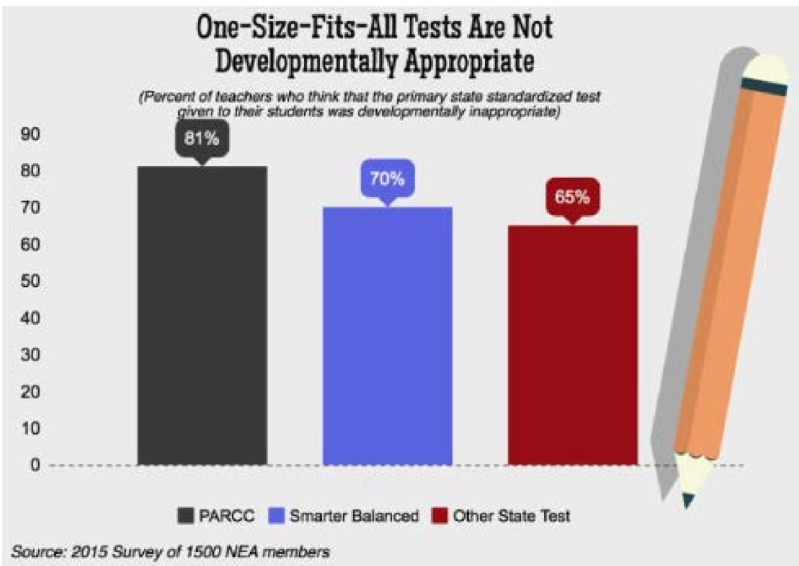


Figure: Student Graph Used for Critique, National Education Association (2016)

The student wrote about this graph:

> The second graph is also a bar chart. It utilized different colors to compare the three options of test given. This graph is communicating the number of teachers who think that standard testing is not development appropriate. The horizontal axis was used to show the three different test that were given as options for the teachers. The vertical axis was used to represent the percentage of teachers that did not agree with the testing style. I like that everything is labeled accordantly. The information is easy, maybe too easy to read. You can see the source on the graph. The way this graph is presented is biased because it only shows the people against it, automatically making it seem that it's a negative thing. The use of different color was not necessary since there are not more than two categories within the same bar. The fact that only three tests where options was insufficient. The graph itself is not poorly display however the information seems to be insufficient to have an unbiased graph. In the article read that there was a subcategory that was not added; the percentage of elementary teachers was higher than a high school teacher. That information could have and should have been added.

Bias is one of the major themes in earlier units, so it makes sense that the student would focus on this. We also talked in class about appropriate use of color, so I was pleased to see that the student included this in their analysis. I would have liked the student to think more closely about the source of the information, too; their source comes from the National Education Association, which is a teacher union / advocacy group; I think the student was starting to see that in their analysis but that there could have been more elaboration.

For part 2, the student discussed how to measure the differences between public and private school performance on SATs. They started by imagining that they would collect data about how students did on the SAT and ACT, and correctly identified the data they were going to look at as quantitative. It turns out, though, that most private schools do not require students to take the SAT or ACT, and so they were unable to locate a study related to that. Instead, they looked at a study involving NAEP test scores:

"The study conducted was a little difficult since private schools were not required to take the SAT or ACT test, and if they do, they are not required to publish the scores; however, there was a testing (NAEP) that could be used to analyze the data. The information obtained was that overall private schools got higher scores (not a huge difference, but there was a difference.) Theyalso saw that the number of students did make a difference; the fewer students the higher the scores. Overall, my assumption was corrected; privates schools score higher, and the fewer the students the higher the scores as well."

Other social issues that students chose to write on included: firearm homicide deaths, Internet pornography, drug abuse, school violence, species extinction, high-risk students, eating disorders, hate crimes, global warming, immigrants separated at the border, marijuana legalization (2 students), women's rights (2 students), and suicide rates.

Conclusion

Overall, my teaching innovation seemed relatively successful; there were obstacles in using the technology because of students' lack of familiarity with the software being used, and I ran into some challenges because I used Microsoft Excel and JMP for my own mathematical research but we used Google Sheets in class, and many of the settings/features are different when doing linear regression in Google Sheets. I found that including social justice themes in the class worked well, too; students seemed engaged and interested in learning about the disparities and broader social issues, and working with data from our own city helped keep the investigation relevant to the students. In future classes, I will introduce spreadsheets earlier when students are studying financial formulas so that they will be more fluent with them when we reach the unit on linear regression. I also will do more research into linear regression and the theory behind it so I can be better prepared to facilitate class conversations about how to find best-fit lines; I found it hard to move students from more superficial understandings to more nuanced understandings, and I think that comes from needing a stronger background in this area myself.

References

Downey, L. (1998). Environmental injustice: Is race or income a better predictor? *Social Science Quarterly*, *79*(4), 766–778.

Economic Policy Institute (2017). Unemployment by state. Retrieved from https://www.epi.org/data/#/?subject=unempstate&r=*

Facts.net (2014). Figure 1: Hate crime incidents by bias type. Retrieved from http://facts.net/wp-content/uploads/2014/12/Hate-Crim-Incidents-by-Bias-Type1.jpg

FBI (2018). Hate Crime Statistics Dataset. Retrieved from http://s3-us-gov-west-1.amazonaws.com/cg-d4b776d0-d898-4153-90c8-8336f86bdfec/hate_crime.zip

McCoy, L. P. (2008). POVERTY: Teaching mathematics and social justice. *The Mathematics Teacher*, *101*(6), 456–461.

National Council of Supervisors of Mathematics and TODOS: Mathematics for All (2016). Mathematics education through the lens of social justice: Acknowledgment, actions, and accountability. Retrieved from https://www.todos-math.org/assets/docs2016/2016Enews/3.pospaper16_wtodos_8pp.pdf

National Education Association (2016, Mar 9). Survey: 70 Percent Of Educators Say State Assessments Not Developmentally Appropriate. NEA Today. Retrieved from http://neatoday.org/2016/02/18/standardized-tests-not-developmentally-appropriate/

Pew Research Center (2013, May 7). After Boston, little change in views of Islam and violence. Retrieved from http://www.people-press.org/2013/05/07/after-boston-little-change-in-views-of-islam-and-violence/

Simpson, E. H. (1949). Measurement of diversity. *Nature*, 163, 688.

Teachman, J. D. (1980). Analysis of Population Diversity: Measures of Qualitative Variation. *Sociological Methods & Research*, *8*(3), 341–362. https://doi.org/10.1177/004912418000800305

Appendix A: Raw Dataset Used for Analysis

	State	Year	Race	Unemployment	Hate Crimes	% of Population
1	Alabama	2010	Black	16.8	14	26
2	Alabama	2010	Hispanic	13.4	1	3.4
3	Alabama	2010	White	8.4	1	67.7
4	Alabama	2011	Black	16.3	38	26.1
5	Alabama	2011	Hispanic	12.7	12	3.7
6	Alabama	2011	White	7.5	21	67.3
7	Alabama	2012	Black	12.9	6	26.2
8	Alabama	2012	Hispanic	10.5	2	3.8
9	Alabama	2012	White	5.9	0	67
10	Alabama	2013	Black	12.2	6	26.2
11	Alabama	2013	Hispanic	9.4	0	3.9
12	Alabama	2013	White	5.2	0	66.8
13	Alabama	2014	Black	12.3	5	26.2
14	Alabama	2014	Hispanic	8.3	2	4
15	Alabama	2014	White	4.9	3	66.6
16	Alaska	2010	Black	5.7	1	3.1
17	Alaska	2010	Hispanic	6.9	0	5.6
18	Alaska	2010	White	6.9	2	64.3
19	Alaska	2011	Black	9.7	2	3.2
20	Alaska	2011	Hispanic	4.4	0	5.6
21	Alaska	2011	White	6.5	1	64.4
22	Alaska	2012	Black	10.1	2	3.2
23	Alaska	2012	Hispanic	5	0	5.7
24	Alaska	2012	White	6.2	1	63.9
25	Alaska	2013	Black	16.7	5	3.3
26	Alaska	2013	Hispanic	8.8	0	5.9
27	Alaska	2013	White	5.4	0	63.5
28	Alaska	2014	Black	8.8	2	3.3
29	Alaska	2014	Hispanic	10	0	6.2
30	Alaska	2014	White	5.7	0	62.9
31	Arizona	2010	Black	10.6	84	3.7
32	Arizona	2010	Hispanic	13.4	25	29
33	Arizona	2010	White	8.7	7	58.7
34	Arizona	2011	Black	15	59	3.8
35	Arizona	2011	Hispanic	12.7	34	29.4
36	Arizona	2011	White	7.8	11	58.2
37	Arizona	2012	Black	8	56	3.8
38	Arizona	2012	Hispanic	10.5	25	29.7
39	Arizona	2012	White	6.9	10	57.7
40	Arizona	2013	Black	14.9	61	3.9
41	Arizona	2013	Hispanic	9.4	17	29.9
42	Arizona	2013	White	5.9	9	57.3
43	Arizona	2014	Black	4.7	93	3.9
44	Arizona	2014	Hispanic	8.3	26	30.1

	State	Year	Race	Unemployment	Hate Crimes	% of Population
45	Arizona	2014	White	5.5	15	56.9
46	Arkansas	2010	Black	16.5	21	15.4
47	Arkansas	2010	Hispanic	7.9	5	5.9
48	Arkansas	2010	White	7.2	11	75.1
49	Arkansas	2011	Black	17.6	15	15.4
50	Arkansas	2011	Hispanic	7.2	2	6.1
51	Arkansas	2011	White	6.7	9	74.8
52	Arkansas	2012	Black	16	11	15.4
53	Arkansas	2012	Hispanic	5.5	3	6.4
54	Arkansas	2012	White	6.1	9	74.5
55	Arkansas	2013	Black	16.5	15	15.4
56	Arkansas	2013	Hispanic	7.7	2	6.6
57	Arkansas	2013	White	6.3	3	74.2
58	Arkansas	2014	Black	10	4	15.5
59	Arkansas	2014	Hispanic	5	0	6.7
60	Arkansas	2014	White	5.5	1	73.9
61	California	2010	Black	18.9	323	5.9
62	California	2010	Hispanic	14.7	119	36.7
63	California	2010	White	10	47	41.2
64	California	2011	Black	19.7	312	5.8
65	California	2011	Hispanic	13.8	88	37.2
66	California	2011	White	9.5	36	40.7
67	California	2012	Black	18	290	5.8
68	California	2012	Hispanic	12.7	88	37.6
69	California	2012	White	8.1	40	40.1
70	California	2013	Black	15.9	287	5.7
71	California	2013	Hispanic	10.2	64	37.9
72	California	2013	White	7.4	38	39.7
73	California	2014	Black	14	243	5.7
74	California	2014	Hispanic	8.5	60	38.2
75	California	2014	White	6.1	28	39.2
76	Colorado	2010	Black	12.9	45	3.7
77	Colorado	2010	Hispanic	13.2	21	20.1
78	Colorado	2010	White	7.4	16	70.6
79	Colorado	2011	Black	14.3	69	3.7
80	Colorado	2011	Hispanic	11.5	12	20.4
81	Colorado	2011	White	7.2	35	70.3
82	Colorado	2012	Black	9.5	46	3.8
83	Colorado	2012	Hispanic	12.6	30	20.6
84	Colorado	2012	White	6.9	33	70
85	Colorado	2013	Black	11.9	40	3.8
86	Colorado	2013	Hispanic	10	15	20.8
87	Colorado	2013	White	5.5	13	69.7
88	Colorado	2014	Black	11.5	34	3.8

	State	Year	Race	Unemployment	Hate Crimes	% of Population
89	Colorado	2014	Hispanic	6.4	4	20.9
90	Colorado	2014	White	4.1	7	69.4
91	Connecticut	2010	Black	15.6	53	9.2
92	Connecticut	2010	Hispanic	17.7	6	12.6
93	Connecticut	2010	White	7.5	6	72.4
94	Connecticut	2011	Black	17.3	48	9.3
95	Connecticut	2011	Hispanic	17.8	7	13
96	Connecticut	2011	White	7.1	12	71.8
97	Connecticut	2012	Black	13.4	51	9.3
98	Connecticut	2012	Hispanic	15.7	10	13.4
99	Connecticut	2012	White	7	10	71.2
100	Connecticut	2013	Black	13.4	49	9.4
101	Connecticut	2013	Hispanic	12.1	13	13.9
102	Connecticut	2013	White	6.4	19	70.5
103	Connecticut	2014	Black	13.1	35	9.5
104	Connecticut	2014	Hispanic	10.9	5	14.3
105	Connecticut	2014	White	5.3	14	69.8
106	Delaware	2010	Black	12.2	7	20.6
107	Delaware	2010	Hispanic	8.6	0	7.6
108	Delaware	2010	White	7.6	2	66.5
109	Delaware	2011	Black	11.5	9	20.8
110	Delaware	2011	Hispanic	8.2	1	7.9
111	Delaware	2011	White	6.2	1	65.9
112	Delaware	2012	Black	10.8	6	20.9
113	Delaware	2012	Hispanic	8.9	2	8.1
114	Delaware	2012	White	5.9	0	65.3
115	Delaware	2013	Black	11.4	12	21
116	Delaware	2013	Hispanic	8.6	0	8.4
117	Delaware	2013	White	5.6	0	64.8
118	Delaware	2014	Black	9.1	7	21.1
119	Delaware	2014	Hispanic	9.3	0	8.6
120	Delaware	2014	White	4.6	1	64.4
121	District Of Columbia	2010	Black	17.2	5	52.3
122	District Of Columbia	2010	Hispanic	8.4	3	8.8
123	District Of Columbia	2010	White	2.4	6	33.4
124	District Of Columbia	2011	Black	19.6	14	51.3
125	District Of Columbia	2011	Hispanic	7.3	4	9
126	District Of Columbia	2011	White	3.3	10	34
127	District Of Columbia	2012	Black	17.4	8	50.4
128	District Of Columbia	2012	Hispanic	7.8	0	9.3
129	District Of Columbia	2012	White	2.7	1	34.5
130	District Of Columbia	2013	Black	15.5	5	49.4
131	District Of Columbia	2013	Hispanic	6.7	2	9.6
132	District Of Columbia	2013	White	3.7	10	35.1

	State	Year	Race	Unemployment	Hate Crimes	% of Population
133	District Of Columbia	2014	Black	15.7	8	48.7
134	District Of Columbia	2014	Hispanic	3.9	0	9.9
135	District Of Columbia	2014	White	2.8	4	35.4
136	Florida	2010	Black	16.8	48	9.2
137	Florida	2010	Hispanic	13.6	0	12.6
138	Florida	2010	White	9.1	13	72.4
139	Florida	2011	Black	17	34	9.3
140	Florida	2011	Hispanic	11.6	0	13
141	Florida	2011	White	7.8	15	71.8
142	Florida	2012	Black	13.6	49	9.3
143	Florida	2012	Hispanic	9.4	0	13.4
144	Florida	2012	White	6.8	23	71.2
145	Florida	2013	Black	12.5	24	9.4
146	Florida	2013	Hispanic	8	0	13.9
147	Florida	2013	White	5.5	16	70.5
148	Florida	2014	Black	10.9	19	9.5
149	Florida	2014	Hispanic	6.6	0	14.3
150	Florida	2014	White	4.9	13	69.8
151	Georgia	2010	Black	16.4	8	30
152	Georgia	2010	Hispanic	11.5	1	8.3
153	Georgia	2010	White	7.6	2	56.8
154	Georgia	2011	Black	15.9	9	30.1
155	Georgia	2011	Hispanic	7.7	0	8.6
156	Georgia	2011	White	7.7	3	56.3
157	Georgia	2012	Black	13.4	11	30.2
158	Georgia	2012	Hispanic	10.1	0	8.8
159	Georgia	2012	White	7.1	3	55.8
160	Georgia	2013	Black	13.5	28	30.3
161	Georgia	2013	Hispanic	6.6	0	8.9
162	Georgia	2013	White	5.8	6	55.4
163	Georgia	2014	Black	12.5	14	30.4
164	Georgia	2014	Hispanic	6	3	9.1
165	Georgia	2014	White	4.5	4	55
166	Hawaii	2010	Black	8.5	.	1.5
167	Hawaii	2010	Hispanic	13.3	.	8.7
168	Hawaii	2010	White	5.9	.	23
169	Hawaii	2011	Black	15.8	.	1.5
170	Hawaii	2011	Hispanic	12.8	.	8.8
171	Hawaii	2011	White	6.6	.	22.9
172	Hawaii	2012	Black	18.6	.	1.5
173	Hawaii	2012	Hispanic	13.5	.	9
174	Hawaii	2012	White	4.9	.	22.8
175	Hawaii	2013	Black	9.1	.	1.6
176	Hawaii	2013	Hispanic	8.1	.	9.3

	State	Year	Race	Unemployment	Hate Crimes	% of Population
177	Hawaii	2013	White	4.4	.	22.8
178	Hawaii	2014	Black	10.3	.	1.8
179	Hawaii	2014	Hispanic	6.7	.	9.6
180	Hawaii	2014	White	4.5	.	22.9
181	Idaho	2010	Black	8	8	0.5
182	Idaho	2010	Hispanic	13.5	2	10.6
183	Idaho	2010	White	8.4	0	84.7
184	Idaho	2011	Black	3.5	8	0.5
185	Idaho	2011	Hispanic	12	0	10.9
186	Idaho	2011	White	8.3	0	84.3
187	Idaho	2012	Black	11.6	2	0.5
188	Idaho	2012	Hispanic	7.1	0	11.2
189	Idaho	2012	White	7.1	1	83.9
190	Idaho	2013	Black	9.9	3	0.5
191	Idaho	2013	Hispanic	9.4	0	11.4
192	Idaho	2013	White	5.7	1	83.7
193	Idaho	2014	Black	6.1	5	0.5
194	Idaho	2014	Hispanic	8	1	11.7
195	Idaho	2014	White	4.2	1	83.3
196	Illinois	2010	Black	17.9	45	14.4
197	Illinois	2010	Hispanic	12.7	7	15.2
198	Illinois	2010	White	7.7	12	64.4
199	Illinois	2011	Black	19.2	49	14.4
200	Illinois	2011	Hispanic	12.2	8	15.5
201	Illinois	2011	White	7.3	6	63.9
202	Illinois	2012	Black	16.3	46	14.3
203	Illinois	2012	Hispanic	10.2	9	15.8
204	Illinois	2012	White	7.3	14	63.5
205	Illinois	2013	Black	17.3	60	14.2
206	Illinois	2013	Hispanic	11.1	9	16
207	Illinois	2013	White	7.3	16	63.3
208	Illinois	2014	Black	14.7	73	14.2
209	Illinois	2014	Hispanic	8.1	12	16.3
210	Illinois	2014	White	5.4	17	62.9
211	Indiana	2010	Black	19.9	12	8.8
212	Indiana	2010	Hispanic	15.3	3	5.6
213	Indiana	2010	White	5.5	3	82.1
214	Indiana	2011	Black	15.5	12	8.8
215	Indiana	2011	Hispanic	11.8	5	5.8
216	Indiana	2011	White	5.1	1	81.8
217	Indiana	2012	Black	20.2	9	8.9
218	Indiana	2012	Hispanic	9.5	7	6
219	Indiana	2012	White	4.6	1	81.5
220	Indiana	2013	Black	17.6	13	8.9

	State	Year	Race	Unemployment	Hate Crimes	% of Population
221	Indiana	2013	Hispanic	6.9	3	6
222	Indiana	2013	White	4.3	2	81.5
223	Indiana	2014	Black	8.5	11	8.9
224	Indiana	2014	Hispanic	8.5	3	6
225	Indiana	2014	White	4.2	2	81.5
226	Iowa	2010	Black	13.3	8	2.7
227	Iowa	2010	Hispanic	10.8	2	4.5
228	Iowa	2010	White	5.5	0	89.4
229	Iowa	2011	Black	16	8	2.8
230	Iowa	2011	Hispanic	11.6	0	4.8
231	Iowa	2011	White	5.1	0	89
232	Iowa	2012	Black	17.1	2	2.8
233	Iowa	2012	Hispanic	9.2	0	5
234	Iowa	2012	White	4.6	1	88.6
235	Iowa	2013	Black	12.3	3	2.9
236	Iowa	2013	Hispanic	7.8	0	5.1
237	Iowa	2013	White	4.3	1	88.2
238	Iowa	2014	Black	15.6	5	3
239	Iowa	2014	Hispanic	8.4	1	5.3
240	Iowa	2014	White	4.2	1	87.8
241	Kansas	2010	Black	13.4	28	5.6
242	Kansas	2010	Hispanic	13	5	9.8
243	Kansas	2010	White	6.5	1	79.1
244	Kansas	2011	Black	14.2	28	5.6
245	Kansas	2011	Hispanic	10.5	5	10.2
246	Kansas	2011	White	5.6	7	78.6
247	Kansas	2012	Black	13.6	35	5.6
248	Kansas	2012	Hispanic	7	5	10.5
249	Kansas	2012	White	4.9	12	78.2
250	Kansas	2013	Black	11.9	22	5.6
251	Kansas	2013	Hispanic	8.1	5	10.7
252	Kansas	2013	White	4.9	12	77.8
253	Kansas	2014	Black	8	31	5.7
254	Kansas	2014	Hispanic	5.4	9	11
255	Kansas	2014	White	4.1	14	77.4
256	Kentucky	2010	Black	19.4	73	7.6
257	Kentucky	2010	Hispanic	14.2	16	2.7
258	Kentucky	2010	White	9.5	39	86.9
259	Kentucky	2011	Black	17.9	63	7.7
260	Kentucky	2011	Hispanic	13.5	10	2.9
261	Kentucky	2011	White	8.9	26	86.6
262	Kentucky	2012	Black	14.3	66	7.7
263	Kentucky	2012	Hispanic	7.5	19	3
264	Kentucky	2012	White	7.5	52	86.3

	State	Year	Race	Unemployment	Hate Crimes	% of Population
265	Kentucky	2013	Black	11.6	60	7.7
266	Kentucky	2013	Hispanic	10.8	12	3.1
267	Kentucky	2013	White	7.6	41	86.1
268	Kentucky	2014	Black	9.6	52	7.8
269	Kentucky	2014	Hispanic	7.6	10	3.2
270	Kentucky	2014	White	6.1	50	85.8
271	Louisiana	2010	Black	12.2	3	31.6
272	Louisiana	2010	Hispanic	8.1	0	3.9
273	Louisiana	2010	White	6.1	1	61.2
274	Louisiana	2011	Black	13	3	31.7
275	Louisiana	2011	Hispanic	12.2	0	4.1
276	Louisiana	2011	White	5.3	0	60.7
277	Louisiana	2012	Black	12.3	1	31.8
278	Louisiana	2012	Hispanic	8.4	0	4.3
279	Louisiana	2012	White	4.6	1	60.3
280	Louisiana	2013	Black	12.3	5	31.8
281	Louisiana	2013	Hispanic	12.6	0	4.4
282	Louisiana	2013	White	4.3	1	60
283	Louisiana	2014	Black	10.4	0	31.9
284	Louisiana	2014	Hispanic	8.6	0	4.6
285	Louisiana	2014	White	4.2	1	59.7
286	Maine	2010	Black	20.6	27	1
287	Maine	2010	Hispanic	12.5	5	1.3
288	Maine	2010	White	7.9	1	94.8
289	Maine	2011	Black	14	18	1
290	Maine	2011	Hispanic	21.2	1	1.4
291	Maine	2011	White	7.6	1	94.6
292	Maine	2012	Black	20.4	17	1
293	Maine	2012	Hispanic	13.6	2	1.3
294	Maine	2012	White	7.4	3	94.4
295	Maine	2013	Black	16.2	10	1.1
296	Maine	2013	Hispanic	9.2	0	1.4
297	Maine	2013	White	6.6	2	94.3
298	Maine	2014	Black	11	10	1.1
299	Maine	2014	Hispanic	8.4	0	1.4
300	Maine	2014	White	5.5	1	94
301	Maryland	2010	Black	11.4	37	28.9
302	Maryland	2010	Hispanic	8.8	4	7.5
303	Maryland	2010	White	5.9	5	55.8
304	Maryland	2011	Black	10.4	18	29
305	Maryland	2011	Hispanic	6.9	5	7.9
306	Maryland	2011	White	5.5	5	55.2
307	Maryland	2012	Black	10.5	20	29
308	Maryland	2012	Hispanic	6.7	1	8.2

	State	Year	Race	Unemployment	Hate Crimes	% of Population
309	Maryland	2012	White	5.4	3	54.7
310	Maryland	2013	Black	10.1	21	29
311	Maryland	2013	Hispanic	5.1	3	8.5
312	Maryland	2013	White	5.4	5	54.1
313	Maryland	2014	Black	8.8	7	29
314	Maryland	2014	Hispanic	5.6	4	8.8
315	Maryland	2014	White	4.6	2	53.6
316	Massachusetts	2010	Black	11.3	105	6
317	Massachusetts	2010	Hispanic	16.1	20	9
318	Massachusetts	2010	White	6.7	28	77.4
319	Massachusetts	2011	Black	11.9	116	6.1
320	Massachusetts	2011	Hispanic	10.3	18	9.3
321	Massachusetts	2011	White	6.1	31	76.9
322	Massachusetts	2012	Black	12.9	86	6.2
323	Massachusetts	2012	Hispanic	9.8	16	9.6
324	Massachusetts	2012	White	6.1	32	76.3
325	Massachusetts	2013	Black	8.6	91	6.3
326	Massachusetts	2013	Hispanic	13.9	22	9.9
327	Massachusetts	2013	White	6.1	44	75.7
328	Massachusetts	2014	Black	10.6	98	6.4
329	Massachusetts	2014	Hispanic	11	15	10.2
330	Massachusetts	2014	White	4.6	16	75
331	Michigan	2010	Black	24	132	14
332	Michigan	2010	Hispanic	13.7	11	4.3
333	Michigan	2010	White	10.5	61	76.9
334	Michigan	2011	Black	20.1	193	13.9
335	Michigan	2011	Hispanic	10.7	12	4.4
336	Michigan	2011	White	8.9	54	76.7
337	Michigan	2012	Black	17.4	302	13.9
338	Michigan	2012	Hispanic	10.8	23	4.4
339	Michigan	2012	White	7.9	117	76.5
340	Michigan	2013	Black	16.9	141	13.9
341	Michigan	2013	Hispanic	13	11	4.5
342	Michigan	2013	White	7.2	61	76.3
343	Michigan	2014	Black	7.7	111	13.8
344	Michigan	2014	Hispanic	8.8	9	4.6
345	Michigan	2014	White	5.7	56	76.1
346	Minnesota	2010	Black	22.1	62	4.8
347	Minnesota	2010	Hispanic	12.3	22	4.5
348	Minnesota	2010	White	6.2	20	83.9
349	Minnesota	2011	Black	20.7	60	4.9
350	Minnesota	2011	Hispanic	8.6	6	4.6
351	Minnesota	2011	White	5.5	11	83.4
352	Minnesota	2012	Black	13.7	45	5

	State	Year	Race	Unemployment	Hate Crimes	% of Population
353	Minnesota	2012	Hispanic	8.4	6	4.7
354	Minnesota	2012	White	5	6	83
355	Minnesota	2013	Black	15.3	70	5.1
356	Minnesota	2013	Hispanic	6.9	4	4.8
357	Minnesota	2013	White	4.1	23	82.6
358	Minnesota	2014	Black	11.7	42	5.3
359	Minnesota	2014	Hispanic	7	8	4.9
360	Minnesota	2014	White	3.2	22	82.1
361	Mississippi	2010	Black	18.5	0	36.9
362	Mississippi	2010	Hispanic	11	9	2.4
363	Mississippi	2010	White	6.9	1	58.5
364	Mississippi	2011	Black	18	0	36.9
365	Mississippi	2011	Hispanic	8	0	2.6
366	Mississippi	2011	White	6.8	0	58.2
367	Mississippi	2012	Black	13.7	4	37
368	Mississippi	2012	Hispanic	11.2	12	2.6
369	Mississippi	2012	White	6.1	1	58
370	Mississippi	2013	Black	13.9	0	37
371	Mississippi	2013	Hispanic	12.1	2	2.7
372	Mississippi	2013	White	5.8	1	57.8
373	Mississippi	2014	Black	12.5	0	37.2
374	Mississippi	2014	Hispanic	6.8	0	2.8
375	Mississippi	2014	White	5.3	0	57.6
376	Missouri	2010	Black	15.1	166	11.4
377	Missouri	2010	Hispanic	13.5	30	3.4
378	Missouri	2010	White	8.6	72	81.4
379	Missouri	2011	Black	16.6	139	11.4
380	Missouri	2011	Hispanic	8.2	10	3.5
381	Missouri	2011	White	7.4	32	81.1
382	Missouri	2012	Black	13	95	11.4
383	Missouri	2012	Hispanic	6.1	10	3.5
384	Missouri	2012	White	6.1	53	80.9
385	Missouri	2013	Black	11.2	94	11.4
386	Missouri	2013	Hispanic	7.3	21	3.7
387	Missouri	2013	White	5.9	39	80.7
388	Missouri	2014	Black	14.4	53	11.4
389	Missouri	2014	Hispanic	8.2	5	3.8
390	Missouri	2014	White	5	42	80.5
391	Montana	2010	Black	0	6	0.4
392	Montana	2010	Hispanic	11.9	0	2.8
393	Montana	2010	White	7.6	8	88.1
394	Montana	2011	Black	0	8	0.4
395	Montana	2011	Hispanic	12.1	3	2.9
396	Montana	2011	White	6.8	2	87.9

	State	Year	Race	Unemployment	Hate Crimes	% of Population
397	Montana	2012	Black	18.1	2	0.4
398	Montana	2012	Hispanic	10.5	1	2.9
399	Montana	2012	White	5.2	8	87.7
400	Montana	2013	Black	18.7	7	0.4
401	Montana	2013	Hispanic	7	0	3.1
402	Montana	2013	White	4.8	16	87.4
403	Montana	2014	Black	9.4	2	0.4
404	Montana	2014	Hispanic	9.3	2	3.2
405	Montana	2014	White	4.2	13	87.2
406	Nebraska	2010	Black	10.4	22	4.3
407	Nebraska	2010	Hispanic	7.5	5	8.4
408	Nebraska	2010	White	4.2	13	83.1
409	Nebraska	2011	Black	15.3	19	4.3
410	Nebraska	2011	Hispanic	7.8	5	8.8
411	Nebraska	2011	White	3.5	4	82.6
412	Nebraska	2012	Black	12.9	3	4.4
413	Nebraska	2012	Hispanic	7.5	1	9.1
414	Nebraska	2012	White	3.1	2	82.1
415	Nebraska	2013	Black	10.4	11	4.5
416	Nebraska	2013	Hispanic	7.7	2	9.4
417	Nebraska	2013	White	3	3	81.7
418	Nebraska	2014	Black	8.8	21	4.5
419	Nebraska	2014	Hispanic	5.8	1	9.7
420	Nebraska	2014	White	2.6	4	81.2
421	Nevada	2010	Black	21	22	7.6
422	Nevada	2010	Hispanic	18.6	10	25.6
423	Nevada	2010	White	12.3	1	55.7
424	Nevada	2011	Black	22.8	26	7.7
425	Nevada	2011	Hispanic	14.5	5	26.1
426	Nevada	2011	White	11.2	3	54.8
427	Nevada	2012	Black	16.6	28	7.8
428	Nevada	2012	Hispanic	13.6	20	26.5
429	Nevada	2012	White	9.6	6	54.1
430	Nevada	2013	Black	15.3	19	7.9
431	Nevada	2013	Hispanic	11.1	7	26.9
432	Nevada	2013	White	8.2	9	53.4
433	Nevada	2014	Black	16.1	6	8
434	Nevada	2014	Hispanic	7.5	3	27.2
435	Nevada	2014	White	7	3	52.7
436	New Hampshire	2010	Black	10.8	8	1
437	New Hampshire	2010	Hispanic	11.9	3	2.7
438	New Hampshire	2010	White	5.8	1	92.7
439	New Hampshire	2011	Black	9.5	11	1
440	New Hampshire	2011	Hispanic	8.8	0	2.8

	State	Year	Race	Unemployment	Hate Crimes	% of Population
441	New Hampshire	2011	White	5.2	0	92.4
442	New Hampshire	2012	Black	7.3	12	1.1
443	New Hampshire	2012	Hispanic	10.5	1	2.8
444	New Hampshire	2012	White	5.4	1	92.2
445	New Hampshire	2013	Black	13.6	9	1.1
446	New Hampshire	2013	Hispanic	6.1	0	2.9
447	New Hampshire	2013	White	5.1	1	91.9
448	New Hampshire	2014	Black	7.2	7	1.1
449	New Hampshire	2014	Hispanic	10	0	3.1
450	New Hampshire	2014	White	4.1	1	91.7
451	New Jersey	2010	Black	15.7	193	12.9
452	New Jersey	2010	Hispanic	10.2	32	16.8
453	New Jersey	2010	White	8.2	17	606
454	New Jersey	2011	Black	16.1	189	12.8
455	New Jersey	2011	Hispanic	11.2	21	17.3
456	New Jersey	2011	White	7.9	22	59.9
457	New Jersey	2012	Black	16	169	12.8
458	New Jersey	2012	Hispanic	10.3	21	17.7
459	New Jersey	2012	White	8.5	10	59.2
460	New Jersey	2013	Black	14.1	152	12.8
461	New Jersey	2013	Hispanic	8.2	21	18.2
462	New Jersey	2013	White	7.3	21	58.5
463	New Jersey	2014	Black	12	131	12.8
464	New Jersey	2014	Hispanic	7.6	15	18.6
465	New Jersey	2014	White	5.5	15	57.8
466	New Mexico	2010	Black	18.8	9	1.8
467	New Mexico	2010	Hispanic	9.1	4	45.4
468	New Mexico	2010	White	6.8	2	41.3
469	New Mexico	2011	Black	19.2	3	1.7
470	New Mexico	2011	Hispanic	9.4	5	45.9
471	New Mexico	2011	White	5.3	2	40.9
472	New Mexico	2012	Black	6.2	0	1.7
473	New Mexico	2012	Hispanic	8.9	0	46.3
474	New Mexico	2012	White	5.6	0	40.5
475	New Mexico	2013	Black	9.1	3	1.8
476	New Mexico	2013	Hispanic	8.5	1	46.7
477	New Mexico	2013	White	4.5	0	40
478	New Mexico	2014	Black	11.1	6	1.8
479	New Mexico	2014	Hispanic	7.5	2	47
480	New Mexico	2014	White	4.3	0	39.6
481	New York	2010	Black	14.5	141	14.5
482	New York	2010	Hispanic	11.8	58	17.1
483	New York	2010	White	6.8	32	59.2
484	New York	2011	Black	13.8	119	14.5

	State	Year	Race	Unemployment	Hate Crimes	% of Population
485	New York	2011	Hispanic	10.6	14	17.4
486	New York	2011	White	6.4	12	58.7
487	New York	2012	Black	13.9	136	14.5
488	New York	2012	Hispanic	11.5	25	17.7
489	New York	2012	White	7.3	20	58.3
490	New York	2013	Black	12.7	108	14.4
491	New York	2013	Hispanic	11	20	17.9
492	New York	2013	White	5.9	27	57.8
493	New York	2014	Black	11.1	87	14.4
494	New York	2014	Hispanic	8.5	13	18.2
495	New York	2014	White	4.7	14	57.3
496	North Carolina	2010	Black	17.5	60	21.2
497	North Carolina	2010	Hispanic	10.7	4	7.8
498	North Carolina	2010	White	8.4	8	66.1
499	North Carolina	2011	Black	19.2	69	21.2
500	North Carolina	2011	Hispanic	9.2	9	8.1
501	North Carolina	2011	White	8	8	65.7
502	North Carolina	2012	Black	15.6	58	21.2
503	North Carolina	2012	Hispanic	8.8	8	8.3
504	North Carolina	2012	White	7.1	20	65.2
505	North Carolina	2013	Black	12.6	48	21.2
506	North Carolina	2013	Hispanic	9.5	8	8.5
507	North Carolina	2013	White	6.1	23	64.9
508	North Carolina	2014	Black	10	76	21.2
509	North Carolina	2014	Hispanic	6.6	16	8.7
510	North Carolina	2014	White	5	18	64.6
511	North Dakota	2010	Black	4.6	0	1
512	North Dakota	2010	Hispanic	7.7	1	2
513	North Dakota	2010	White	3	1	89.4
514	North Dakota	2011	Black	13.2	7	1
515	North Dakota	2011	Hispanic	9.2	0	2
516	North Dakota	2011	White	2.4	6	89.2
517	North Dakota	2012	Black	11.4	8	1.2
518	North Dakota	2012	Hispanic	4	2	2.1
519	North Dakota	2012	White	2.2	9	88.8
520	North Dakota	2013	Black	8.6	13	1.3
521	North Dakota	2013	Hispanic	5.1	4	2.3
522	North Dakota	2013	White	2.2	7	88.3
523	North Dakota	2014	Black	12.2	7	1.3
524	North Dakota	2014	Hispanic	5.6	5	2.3
525	North Dakota	2014	White	2.1	12	88.3
526	Ohio	2010	Black	16.7	142	12
527	Ohio	2010	Hispanic	11.6	12	2.9
528	Ohio	2010	White	9.1	60	81.6

	State	Year	Race	Unemployment	Hate Crimes	% of Population
529	Ohio	2011	Black	17	108	12
530	Ohio	2011	Hispanic	9	6	3
531	Ohio	2011	White	7.6	66	81.4
532	Ohio	2012	Black	14.6	117	12
533	Ohio	2012	Hispanic	8.8	12	3.1
534	Ohio	2012	White	6	43	81.1
535	Ohio	2013	Black	14.7	169	12
536	Ohio	2013	Hispanic	14.2	16	3.2
537	Ohio	2013	White	6.6	81	80.8
538	Ohio	2014	Black	11.9	168	12
539	Ohio	2014	Hispanic	5.9	14	3.3
540	Ohio	2014	White	4.7	101	80.5
541	Oklahoma	2010	Black	13.3	53	7.2
542	Oklahoma	2010	Hispanic	10.1	10	8.2
543	Oklahoma	2010	White	5.7	2	69.6
544	Oklahoma	2011	Black	11.7	21	7.2
545	Oklahoma	2011	Hispanic	12.6	16	8.6
546	Oklahoma	2011	White	4.7	0	69.1
547	Oklahoma	2012	Black	9.1	9	7.1
548	Oklahoma	2012	Hispanic	3.7	2	8.8
549	Oklahoma	2012	White	4.2	3	68.7
550	Oklahoma	2013	Black	8.3	25	7.1
551	Oklahoma	2013	Hispanic	8.2	6	9.1
552	Oklahoma	2013	White	4.5	16	68.2
553	Oklahoma	2014	Black	7.2	9	7.1
554	Oklahoma	2014	Hispanic	6	7	9.4
555	Oklahoma	2014	White	3.7	8	67.8
556	Oregon	2010	Black	11.7	57	1.7
557	Oregon	2010	Hispanic	11.6	18	11.2
558	Oregon	2010	White	10.9	10	79.3
559	Oregon	2011	Black	20.3	52	1.7
560	Oregon	2011	Hispanic	13.5	15	11.5
561	Oregon	2011	White	8.8	11	78.8
562	Oregon	2012	Black	19	19	1.7
563	Oregon	2012	Hispanic	11.5	10	11.7
564	Oregon	2012	White	8.4	3	78.4
565	Oregon	2013	Black	19.2	31	1.7
566	Oregon	2013	Hispanic	11.1	10	11.9
567	Oregon	2013	White	7.3	6	78
568	Oregon	2014	Black	12.9	7	1.7
569	Oregon	2014	Hispanic	9.7	8	12.1
570	Oregon	2014	White	6.5	2	77.6
571	Pennsylvania	2010	Black	15.8	31	10.4
572	Pennsylvania	2010	Hispanic	15.5	7	5.2

	State	Year	Race	Unemployment	Hate Crimes	% of Population
573	Pennsylvania	2010	White	7.5	4	80.3
574	Pennsylvania	2011	Black	12.9	6	10.4
575	Pennsylvania	2011	Hispanic	14.4	2	5.5
576	Pennsylvania	2011	White	6.7	3	79.8
577	Pennsylvania	2012	Black	14.5	21	10.4
578	Pennsylvania	2012	Hispanic	12.8	0	5.7
579	Pennsylvania	2012	White	6.6	2	79.4
580	Pennsylvania	2013	Black	14.2	39	10.5
581	Pennsylvania	2013	Hispanic	12.3	1	5.9
582	Pennsylvania	2013	White	6.4	9	79
583	Pennsylvania	2014	Black	10.8	22	10.5
584	Pennsylvania	2014	Hispanic	9.6	5	6.1
585	Pennsylvania	2014	White	4.8	11	78.5
586	Rhode Island	2010	Black	14.4	9	5.2
587	Rhode Island	2010	Hispanic	21.7	1	11.8
588	Rhode Island	2010	White	9.7	1	77.4
589	Rhode Island	2011	Black	18.1	2	5.2
590	Rhode Island	2011	Hispanic	21.6	7	12.1
591	Rhode Island	2011	White	9.1	1	76.9
592	Rhode Island	2012	Black	15.2	3	5.2
593	Rhode Island	2012	Hispanic	19.3	1	12.5
594	Rhode Island	2012	White	8.9	1	76.4
595	Rhode Island	2013	Black	13.3	4	5.3
596	Rhode Island	2013	Hispanic	20.9	1	12.9
597	Rhode Island	2013	White	7.2	0	75.7
598	Rhode Island	2014	Black	11.5	0	5.2
599	Rhode Island	2014	Hispanic	16.2	1	13.3
600	Rhode Island	2014	White	6.2	1	75.1
601	South Carolina	2010	Black	18.3	41	28
602	South Carolina	2010	Hispanic	10.9	4	4.6
603	South Carolina	2010	White	8.3	20	64.5
604	South Carolina	2011	Black	16.9	42	27.8
605	South Carolina	2011	Hispanic	12.2	13	4.9
606	South Carolina	2011	White	7.9	26	64.3
607	South Carolina	2012	Black	16.2	33	27.7
608	South Carolina	2012	Hispanic	8.1	3	5
609	South Carolina	2012	White	6.8	26	64.1
610	South Carolina	2013	Black	11.8	19	27.6
611	South Carolina	2013	Hispanic	5.6	0	5.2
612	South Carolina	2013	White	6	18	64
613	South Carolina	2014	Black	9.8	17	27.4
614	South Carolina	2014	Hispanic	9	4	5.3
615	South Carolina	2014	White	5.1	10	63.9
616	South Dakota	2010	Black	10.9	8	1.1

	State	Year	Race	Unemployment	Hate Crimes	% of Population
617	South Dakota	2010	Hispanic	7.2	11	2.6
618	South Dakota	2010	White	4.1	18	85.4
619	South Dakota	2011	Black	8	10	1.1
620	South Dakota	2011	Hispanic	9.3	0	2.7
621	South Dakota	2011	White	3.9	8	85
622	South Dakota	2012	Black	11.9	12	1.2
623	South Dakota	2012	Hispanic	8.7	3	2.8
624	South Dakota	2012	White	3.7	7	84.5
625	South Dakota	2013	Black	7	5	1.4
626	South Dakota	2013	Hispanic	7.5	0	3
627	South Dakota	2013	White	2.7	2	84.1
628	South Dakota	2014	Black	12.2	5	1.5
629	South Dakota	2014	Hispanic	6.2	1	3.2
630	South Dakota	2014	White	2.7	3	83.6
631	Tennessee	2010	Black	14.7	82	16.5
632	Tennessee	2010	Hispanic	8.5	10	4.2
633	Tennessee	2010	White	8.3	19	76.2
634	Tennessee	2011	Black	14.9	65	16.5
635	Tennessee	2011	Hispanic	10.6	7	4.4
636	Tennessee	2011	White	7.8	20	75.9
637	Tennessee	2012	Black	13.5	89	16.6
638	Tennessee	2012	Hispanic	5.5	17	4.5
639	Tennessee	2012	White	6.9	100	75.6
640	Tennessee	2013	Black	15.1	58	16.7
641	Tennessee	2013	Hispanic	8	10	4.7
642	Tennessee	2013	White	6.5	10	75.3
643	Tennessee	2014	Black	11.5	46	16.7
644	Tennessee	2014	Hispanic	4.4	7	4.8
645	Tennessee	2014	White	5.7	28	75
646	Texas	2010	Black	13.2	119	11.6
647	Texas	2010	Hispanic	9.4	44	36.7
648	Texas	2010	White	5.9	16	46.4
649	Texas	2011	Black	13.5	97	11.5
650	Texas	2011	Hispanic	8.9	52	37.2
651	Texas	2011	White	5.7	12	45.8
652	Texas	2012	Black	11.1	106	11.5
653	Texas	2012	Hispanic	7.7	51	37.6
654	Texas	2012	White	4.7	19	45.3
655	Texas	2013	Black	10.7	85	11.5
656	Texas	2013	Hispanic	6.9	47	37.9
657	Texas	2013	White	4.6	16	44.8
658	Texas	2014	Black	9.5	79	11.6
659	Texas	2014	Hispanic	5.3	29	38.2
660	Texas	2014	White	3.7	35	44.3

	State	Year	Race	Unemployment	Hate Crimes	% of Population
661	Utah	2010	Black	8.8	9	0.9
662	Utah	2010	Hispanic	12.6	5	12.3
663	Utah	2010	White	7.6	6	81.2
664	Utah	2011	Black	3.4	9	1
665	Utah	2011	Hispanic	8.4	6	12.7
666	Utah	2011	White	6.7	17	80.7
667	Utah	2012	Black	18	17	1
668	Utah	2012	Hispanic	7.8	9	12.9
669	Utah	2012	White	5.1	20	80.4
670	Utah	2013	Black	10.9	14	1
671	Utah	2013	Hispanic	5.7	4	13.1
672	Utah	2013	White	3.9	27	80.1
673	Utah	2014	Black	2.7	6	1
674	Utah	2014	Hispanic	4.4	4	13.3
675	Utah	2014	White	3.7	14	79.8
676	Vermont	2010	Black	13.1	4	0.8
677	Vermont	2010	Hispanic	4	1	1.5
678	Vermont	2010	White	6.1	1	94.6
679	Vermont	2011	Black	13.5	4	0.8
680	Vermont	2011	Hispanic	4.3	0	1.5
681	Vermont	2011	White	5.8	1	94.4
682	Vermont	2012	Black	9.8	6	0.9
683	Vermont	2012	Hispanic	4.3	0	1.5
684	Vermont	2012	White	4.9	2	94.2
685	Vermont	2013	Black	11.7	5	1
686	Vermont	2013	Hispanic	14.2	0	1.6
687	Vermont	2013	White	4	3	94.1
688	Vermont	2014	Black	0	4	1
689	Vermont	2014	Hispanic	4	0	1.6
690	Vermont	2014	White	4.2	2	93.9
691	Virginia	2010	Black	11.3	76	19.3
692	Virginia	2010	Hispanic	6.9	19	7.3
693	Virginia	2010	White	6.5	24	65.7
694	Virginia	2011	Black	11.5	65	19.2
695	Virginia	2011	Hispanic	5.7	11	7.6
696	Virginia	2011	White	5.2	10	65.2
697	Virginia	2012	Black	10.1	68	19.1
698	Virginia	2012	Hispanic	3.3	7	7.9
699	Virginia	2012	White	5.2	7	64.8
700	Virginia	2013	Black	9.2	58	19
701	Virginia	2013	Hispanic	5.2	4	8.1
702	Virginia	2013	White	4.7	7	64.3
703	Virginia	2014	Black	8	48	18.9
704	Virginia	2014	Hispanic	6.1	5	8.4

	State	Year	Race	Unemployment	Hate Crimes	% of Population
705	Virginia	2014	White	4.5	16	63.9
706	Washington	2010	Black	20.8	82	3.4
707	Washington	2010	Hispanic	15.8	23	10.5
708	Washington	2010	White	9	19	73.7
709	Washington	2011	Black	19.3	57	3.4
710	Washington	2011	Hispanic	14.7	21	10.9
711	Washington	2011	White	8.5	12	73.1
712	Washington	2012	Black	14	69	3.4
713	Washington	2012	Hispanic	11.3	15	11.2
714	Washington	2012	White	8	27	72.5
715	Washington	2013	Black	14.7	70	3.5
716	Washington	2013	Hispanic	8.9	19	11.5
717	Washington	2013	White	6.5	46	71.9
718	Washington	2014	Black	14.3	68	3.5
719	Washington	2014	Hispanic	9	12	11.7
720	Washington	2014	White	5.3	55	71.3
721	West Virginia	2010	Black	18.9	12	3.2
722	West Virginia	2010	Hispanic	9	1	1.1
723	West Virginia	2010	White	8.5	12	93.4
724	West Virginia	2011	Black	22	12	3.1
725	West Virginia	2011	Hispanic	5.6	1	1.2
726	West Virginia	2011	White	7.5	1	93.2
727	West Virginia	2012	Black	7.9	6	3.1
728	West Virginia	2012	Hispanic	6.9	0	1.2
729	West Virginia	2012	White	7.4	13	93
730	West Virginia	2013	Black	6.8	12	3.1
731	West Virginia	2013	Hispanic	6.6	3	1.3
732	West Virginia	2013	White	6.7	31	92.9
733	West Virginia	2014	Black	10	8	3.2
734	West Virginia	2014	Hispanic	3.7	0	1.3
735	West Virginia	2014	White	6.5	9	92.7
736	Wisconsin	2010	Black	25.3	15	6.1
737	Wisconsin	2010	Hispanic	9.9	7	5.5
738	Wisconsin	2010	White	7.5	22	84
739	Wisconsin	2011	Black	24.9	19	6.1
740	Wisconsin	2011	Hispanic	12.1	6	5.7
741	Wisconsin	2011	White	6.3	20	83.6
742	Wisconsin	2012	Black	19.3	26	6.1
743	Wisconsin	2012	Hispanic	11.4	3	5.9
744	Wisconsin	2012	White	5.9	10	83.3
745	Wisconsin	2013	Black	15	15	6.1
746	Wisconsin	2013	Hispanic	14.6	4	6.1
747	Wisconsin	2013	White	5.4	7	83
748	Wisconsin	2014	Black	19.9	15	6.1

	State	Year	Race	Unemployment	Hate Crimes	% of Population
749	Wisconsin	2014	Hispanic	9.1	4	6.2
750	Wisconsin	2014	White	4.3	12	82.7
751	Wyoming	2010	Black	4.2	2	0.7
752	Wyoming	2010	Hispanic	10.9	0	8.4
753	Wyoming	2010	White	6.2	0	86.3
754	Wyoming	2011	Black	21.7	1	0.8
755	Wyoming	2011	Hispanic	8.1	0	8.4
756	Wyoming	2011	White	5.3	0	86.3
757	Wyoming	2012	Black	9.8	1	0.8
758	Wyoming	2012	Hispanic	8.9	1	8.9
759	Wyoming	2012	White	4.7	0	85.6
760	Wyoming	2013	Black	17.1	0	85.2
761	Wyoming	2013	Hispanic	5.4	1	9.2
762	Wyoming	2013	White	4.3	0	85.2
763	Wyoming	2014	Black	10.1	0	1
764	Wyoming	2014	Hispanic	3.8	0	9.4
765	Wyoming	2014	White	4.1	0	84.8

Appendix B: Unemployment Discrepancy, Hate Crime Discrepancy, Combined Discrepancy, and Racial Diversity by State, from 2010-2014.

	State	Year	Unemployment Discrepancy	Hate Crime Discrepancy	Combined Discrepancy	Racial Diversity
1	Alabama	2010	16.8	1.31971165	4.70862567	0.66144132
2	Alabama	2011	17.6	1.51884896	5.17027482	0.66886463
3	Alabama	2012	14	1.14736885	4.0078877	0.67261983
4	Alabama	2013	14	1.14736885	4.0078877	0.67506318
5	Alabama	2014	14.8	1.09096846	4.01825002	0.67750239
6	Alaska	2010	2.4	1.18053737	1.68323786	0.32469694
7	Alaska	2011	10.6	1.36806791	3.80808611	0.32733136
8	Alaska	2012	10.2	1.3679588	3.73539553	0.33224588
9	Alaska	2013	22.6	1.84945074	6.46510531	0.34265102
10	Alaska	2014	8.6	1.37143308	3.4342866	0.35370372
11	Arizona	2010	9.4	7.65444548	8.48243995	0.72784284
12	Arizona	2011	14.4	5.7808978	9.12386586	0.73400878
13	Arizona	2012	7.2	5.64507636	6.37530782	0.73789892
14	Arizona	2013	18	5.91399277	10.3175515	0.74224535
15	Arizona	2014	7.2	7.28498	7.24236536	0.74502137
16	Arkansas	2010	18.6	1.61986305	5.48903022	0.54573247
17	Arkansas	2011	21.8	1.45883764	5.63938477	0.55063518
18	Arkansas	2012	21	1.32750246	5.27991967	0.55727332
19	Arkansas	2013	20.4	1.53259114	5.59149885	0.56212153
20	Arkansas	2014	10	1.1549868	3.39850968	0.56666714
21	California	2010	17.8	8.7853755	12.5051863	0.84229271
22	California	2011	20.4	9.45547382	13.8885444	0.84182714
23	California	2012	19.8	8.67071055	13.1026741	0.84266342
24	California	2013	17	8.82967875	12.2517158	0.84175567
25	California	2014	15.8	8.65257055	11.6923314	0.84219352
26	Colorado	2010	11.6	4.86492367	7.51219772	0.59070108
27	Colorado	2011	14.2	5.56211239	8.88718155	0.59577102
28	Colorado	2012	11.4	4.29672647	6.99876288	0.60134929
29	Colorado	2013	12.8	4.55279947	7.63386096	0.6051151
30	Colorado	2014	14.8	4.33826633	8.01288598	0.60766973
31	Connecticut	2010	20.4	3.39065322	8.31680982	0.57278862
32	Connecticut	2011	21.4	3.03180594	8.05485239	0.58342528
33	Connecticut	2012	17.4	3.18546046	7.44493197	0.59231662
34	Connecticut	2013	14	2.88248717	6.35254441	0.60464469
35	Connecticut	2014	15.6	2.47836465	6.21791674	0.61537434
36	Delaware	2010	9.2	1.19155828	3.31094189	0.67969657
37	Delaware	2011	10.6	1.25817625	3.65194034	0.68910937
38	Delaware	2012	9.8	1.18323406	3.40524504	0.69597717
39	Delaware	2013	11.6	1.35164641	3.95968413	0.70372023
40	Delaware	2014	9.4	1.19808599	3.35589158	0.70949236
41	District Of Columbia	2010	29.6	0.95192365	5.30819557	0.84017133
42	District Of Columbia	2011	32.6	0.98904193	5.67827148	0.84742294
43	District Of Columbia	2012	29.4	1.08238567	5.64111149	0.85479127
44	District Of Columbia	2013	23.6	0.90226688	4.61448788	0.86229066

	State	Year	Unemployment Discrepancy	Hate Crime Discrepancy	Combined Discrepancy	Racial Diversity
45	District Of Columbia	2014	25.8	1.03048283	5.15620567	0.86800702
46	Florida	2010	15.4	3.02872097	6.82951704	0.57278862
47	Florida	2011	18.4	2.45700729	6.72375893	0.58342528
48	Florida	2012	13.6	2.8210436	6.19404496	0.59231662
49	Florida	2013	14	2.03170702	5.33328213	0.60464469
50	Florida	2014	12	1.85622618	4.71960954	0.61537434
51	Georgia	2010	17.6	1.14399002	4.48711759	0.80421406
52	Georgia	2011	16.4	1.15003037	4.34286749	0.81030582
53	Georgia	2012	12.6	1.18785865	3.86872317	0.8151605
54	Georgia	2013	15.4	1.44448004	4.71645976	0.81840642
55	Georgia	2014	16	1.22841952	4.43336355	0.82275636
56	Hawaii	2010	14.8	.	.	0.67403651
57	Hawaii	2011	18.4	.	.	0.67790136
58	Hawaii	2012	27.4	.	.	0.68419771
59	Hawaii	2013	9.4	.	.	0.69578846
60	Hawaii	2014	11.6	.	.	0.70975529
61	Idaho	2010	11	6.61148902	8.52797627	0.30905658
62	Idaho	2011	17	6.61148902	10.6016656	0.31658166
63	Idaho	2012	9	2.90101194	5.10970718	0.3240588
64	Idaho	2013	8.4	3.63044664	5.52229588	0.32881843
65	Idaho	2014	7.6	4.90689473	6.10675036	0.33621118
66	Illinois	2010	20.4	2.29514947	6.84259083	0.72152105
67	Illinois	2011	23.8	2.53027058	7.76018297	0.7275642
68	Illinois	2012	18	2.28543495	6.41387786	0.73186843
69	Illinois	2013	20	2.59117884	7.19885941	0.73397352
70	Illinois	2014	18.6	2.85904728	7.29234389	0.73934609
71	Indiana	2010	28.8	1.7324585	7.06362547	0.39674193
72	Indiana	2011	20.8	1.76009356	6.05061534	0.40202045
73	Indiana	2012	31.2	1.58043919	7.02208677	0.40926142
74	Indiana	2013	26.6	1.79342614	6.90689041	0.40926142
75	Indiana	2014	8.6	1.68250412	3.80388425	0.40926142
76	Iowa	2010	15.6	2.50426342	6.25032073	0.21084256
77	Iowa	2011	21.8	2.45948295	7.32234445	0.22177642
78	Iowa	2012	25	1.42169339	5.96173925	0.22761747
79	Iowa	2013	16	1.59357251	5.04947128	0.23352791
80	Iowa	2014	22.8	1.90853526	6.59656001	0.24189163
81	Kansas	2010	13.8	3.27438804	6.72209453	0.42765432
82	Kansas	2011	17.2	3.11936854	7.3248303	0.43730699
83	Kansas	2012	17.4	3.40584972	7.69816765	0.44458414
84	Kansas	2013	14	2.63198177	6.07023433	0.44994528
85	Kansas	2014	7.8	3.09782811	4.91559348	0.45916739
86	Kentucky	2010	19.8	3.77002008	8.63981468	0.29072994
87	Kentucky	2011	18	3.68077096	8.13964847	0.29857301
88	Kentucky	2012	13.6	3.29187689	6.69100334	0.30178871

	State	Year	Unemployment Discrepancy	Hate Crime Discrepancy	Combined Discrepancy	Racial Diversity
89	Kentucky	2013	8	3.28576901	5.12700225	0.30472512
90	Kentucky	2014	7	2.86283334	4.47658725	0.31016068
91	Louisiana	2010	12.2	1.05091285	3.5806615	0.73656304
92	Louisiana	2011	15.4	1.06213603	4.04436582	0.74193562
93	Louisiana	2012	15.4	1.00972329	3.9433157	0.74687828
94	Louisiana	2013	16.6	1.0901713	4.25403849	0.74945215
95	Louisiana	2014	12.4	0.98898664	3.50191867	0.75394838
96	Maine	2010	25.4	9.15659291	15.2504905	0.06979119
97	Maine	2011	27.2	7.0706265	13.8679862	0.07283665
98	Maine	2012	26	6.72651882	13.224579	0.07007461
99	Maine	2013	19.2	4.60479675	9.40277075	0.07597137
100	Maine	2014	11	4.6368498	7.14180284	0.07620285
101	Maryland	2010	11	1.6361086	4.24231006	0.79328749
102	Maryland	2011	9.8	1.30225179	3.57240361	0.80141611
103	Maryland	2012	10.2	1.3690093	3.73682951	0.80727384
104	Maryland	2013	10	1.35556764	3.68180342	0.81350351
105	Maryland	2014	8.4	1.12718794	3.07707307	0.81923303
106	Massachusetts	2010	18.8	5.69352701	10.3459319	0.42692697
107	Massachusetts	2011	11.6	5.88202884	8.26023816	0.43700473
108	Massachusetts	2012	13.6	4.78803014	8.06952352	0.44741766
109	Massachusetts	2013	15.6	4.56929657	8.44280916	0.457768
110	Massachusetts	2014	12.8	5.65405806	8.5071701	0.46848363
111	Michigan	2010	27	3.23388518	9.34424421	0.48575423
112	Michigan	2011	22.4	4.24141054	9.74718401	0.48690416
113	Michigan	2012	19	4.32192137	9.06181582	0.48773901
114	Michigan	2013	19.4	3.3723068	8.08843322	0.49056265
115	Michigan	2014	6.2	3.00523353	4.31653193	0.49171748
116	Minnesota	2010	31.8	5.01711927	12.6310883	0.27694492
117	Minnesota	2011	30.4	5.15420612	12.5175024	0.28324494
118	Minnesota	2012	17.4	4.43056104	8.78019146	0.28927221
119	Minnesota	2013	22.4	5.10023977	10.6885626	0.29529993
120	Minnesota	2014	17	3.67269727	7.90163614	0.3040359
121	Mississippi	2010	23.2	0.9887639	4.78950127	0.74887086
122	Mississippi	2011	22.4	1	4.73286383	0.75267697
123	Mississippi	2012	15.2	1.05869796	4.01150957	0.75364065
124	Mississippi	2013	16.2	0.98862975	4.00197475	0.75567968
125	Mississippi	2014	14.4	1	3.79473319	0.75841508
126	Missouri	2010	13	4.08537449	7.28765178	0.40309732
127	Missouri	2011	18.4	4.47301982	9.07213121	0.4063444
128	Missouri	2012	13.8	3.16813112	6.61212594	0.4070687
129	Missouri	2013	10.6	3.38696022	5.99180927	0.41211575
130	Missouri	2014	18.8	2.39751061	6.71365769	0.41499854
131	Montana	2010	23.8	5.9921361	11.9420618	0.10186559
132	Montana	2011	24.2	7.49834903	13.4707107	0.10504314

	State	Year	Unemployment Discrepancy	Hate Crime Discrepancy	Combined Discrepancy	Racial Diversity
133	Montana	2012	25.8	3.11524784	8.96512099	0.10526627
134	Montana	2013	27.8	6.25328777	13.1848929	0.11151412
135	Montana	2014	10.4	3.00977023	5.59478422	0.1146927
136	Nebraska	2010	12.4	3.03559121	6.13525313	0.3567878
137	Nebraska	2011	23.6	2.98927874	8.39922487	0.36683995
138	Nebraska	2012	19.6	1.39171659	5.2228005	0.37695966
139	Nebraska	2013	14.8	2.22658128	5.74050546	0.38665618
140	Nebraska	2014	12.4	3.07819457	6.17815609	0.3944629
141	Nevada	2010	17.4	2.44624623	6.52416159	0.77581135
142	Nevada	2011	23.2	2.58222807	7.74000589	0.78467024
143	Nevada	2012	14	2.57478406	6.00391346	0.79172596
144	Nevada	2013	14.2	2.04011463	5.38234408	0.79859858
145	Nevada	2014	18.2	1.39957329	5.04700247	0.80476185
146	New Hampshire	2010	12.2	4.29590928	7.23948156	0.11159738
147	New Hampshire	2011	8.6	5.24148279	6.71392225	0.11472979
148	New Hampshire	2012	10.2	5.17760696	7.26715839	0.11780782
149	New Hampshire	2013	17	4.35330395	8.60268372	0.12095172
150	New Hampshire	2014	11.8	3.75769295	6.65888706	0.12674503
151	New Jersey	2010	15	6.2234921	9.66190362	0.13522099
152	New Jersey	2011	16.4	5.10390688	9.14899299	0.74978889
153	New Jersey	2012	15	5.28525989	8.90386985	0.75769473
154	New Jersey	2013	13.6	4.47738029	7.80335646	0.7664405
155	New Jersey	2014	13	4.30094198	7.47744914	0.77407046
156	New Mexico	2010	24	3.19945204	8.76281056	0.77796802
157	New Mexico	2011	27.8	1.90813883	7.2832863	0.77558939
158	New Mexico	2012	6.6	1	2.56904652	0.77476204
159	New Mexico	2013	9.2	1.92299943	4.20613774	0.77527913
160	New Mexico	2014	13.6	2.6579577	6.01233937	0.77435454
161	New York	2010	15.4	3.64579999	7.49301808	0.77092632
162	New York	2011	14.8	3.8805025	7.57835318	0.77658509
163	New York	2012	13.2	3.9088607	7.18310248	0.78162816
164	New York	2013	13.6	3.22577403	6.62348298	0.78518011
165	New York	2014	12.8	3.17560909	6.37556244	0.79066717
166	North Carolina	2010	18.2	2.26848344	6.42544929	0.6907091
167	North Carolina	2011	22.4	2.43208662	7.3809715	0.69697396
168	North Carolina	2012	17	2.0143343	5.85181024	0.70227663
169	North Carolina	2013	13	1.79756265	4.83407846	0.70656799
170	North Carolina	2014	10	2.34272826	4.84017382	0.71083564
171	North Dakota	2010	9.4	0.99261171	3.0545949	0.09494294
172	North Dakota	2011	21.6	3.83011601	9.09563114	0.09514354
173	North Dakota	2012	18.4	3.64575205	8.19035028	0.10453161
174	North Dakota	2013	12.8	4.7008204	7.75696468	0.11397756
175	North Dakota	2014	20.2	3.16128032	7.99111146	0.11397756
176	Ohio	2010	15.2	3.79586641	7.59586529	0.40290155

	State	Year	Unemployment Discrepancy	Hate Crime Discrepancy	Combined Discrepancy	Racial Diversity
177	Ohio	2011	18.8	3.12428958	7.66398357	0.40579105
178	Ohio	2012	17.2	3.66807628	7.94297878	0.40903934
179	Ohio	2013	16.2	3.8425552	7.88982853	0.41229167
180	Ohio	2014	14.4	3.53731449	7.13703921	0.41554801
181	Oklahoma	2010	15.2	4.04240797	7.83866067	0.46956955
182	Oklahoma	2011	15.8	2.48472163	6.2656685	0.48017414
183	Oklahoma	2012	10.8	1.67752914	4.2564439	0.48405094
184	Oklahoma	2013	7.6	2.37581513	4.24925817	0.49251336
185	Oklahoma	2014	7	1.60233017	3.34907617	0.5004327
186	Oregon	2010	1.6	9.79656758	3.95910446	0.36773189
187	Oregon	2011	23	9.15904438	14.5140629	0.3756061
188	Oregon	2012	21.2	5.16188971	10.4609781	0.38106782
189	Oregon	2013	23.8	6.83296871	12.7524372	0.38651651
190	Oregon	2014	12.8	2.91975217	6.11333197	0.39195184
191	Pennsylvania	2010	16.6	2.4316626	6.35339273	0.42626519
192	Pennsylvania	2011	15.4	1.32186989	4.51185065	0.43435763
193	Pennsylvania	2012	15.8	2.05460467	5.69760948	0.43999452
194	Pennsylvania	2013	15.6	2.6164165	6.38874772	0.44748691
195	Pennsylvania	2014	12	1.94607895	4.83248874	0.45349906
196	Rhode Island	2010	24	1.93704599	6.81829185	0.46361947
197	Rhode Island	2011	25	1.23162555	5.54893132	0.47104345
198	Rhode Island	2012	20.8	1.34310079	5.28549869	0.48017292
199	Rhode Island	2013	27.4	1.45480478	6.3136084	0.49202979
200	Rhode Island	2014	20	0.9912203	4.45246066	0.49943499
201	South Carolina	2010	20	1.52380494	5.52051617	0.71003488
202	South Carolina	2011	18	1.47306722	5.14929219	0.71383675
203	South Carolina	2012	18.8	1.34450196	5.02758758	0.71542565
204	South Carolina	2013	12.4	1.20197464	3.86063279	0.71803497
205	South Carolina	2014	9.4	1.25215825	3.43078526	0.71844901
206	South Dakota	2010	13.6	3.60073112	6.99785276	0.12048657
207	South Dakota	2011	10.8	4.39788816	6.89182067	0.12401464
208	South Dakota	2012	16.4	4.69049704	8.77064146	0.1307517
209	South Dakota	2013	9.6	2.71162641	5.10211853	0.14334578
210	South Dakota	2014	19	2.59621301	7.02339286	0.15303025
211	Tennessee	2010	12.8	2.83691859	6.0259902	0.52610492
212	Tennessee	2011	14.2	2.48159681	5.9362172	0.53112087
213	Tennessee	2012	16	1.95750138	5.5964294	0.53573296
214	Tennessee	2013	17.2	2.49823555	6.55512406	0.54216551
215	Tennessee	2014	14.2	1.95516496	5.26909313	0.54530108
216	Texas	2010	14.6	4.12299099	7.75858676	0.89210969
217	Texas	2011	15.6	3.82337027	7.7229901	0.89300747
218	Texas	2012	12.8	3.72807668	6.90792165	0.8943517
219	Texas	2013	12.2	3.3687538	6.41083429	0.89556371
220	Texas	2014	11.6	2.67013876	5.56539393	0.89756641

	State	Year	Unemployment Discrepancy	Hate Crime Discrepancy	Combined Discrepancy	Racial Diversity
221	Utah	2010	10	4.71651789	6.86769095	0.36456052
222	Utah	2011	10	4.08619713	6.39233692	0.37647116
223	Utah	2012	25.8	5.92283854	12.3616032	0.38137575
224	Utah	2013	14	5.01136693	8.37610512	0.38625975
225	Utah	2014	3.4	3.28547925	3.34224916	0.39112302
226	Vermont	2010	18.2	3.27886093	7.72497695	0.06990067
227	Vermont	2011	18.4	3.27881248	7.76724853	0.07004253
228	Vermont	2012	11	3.83402501	6.49417239	0.07311639
229	Vermont	2013	20.4	3.23356128	8.12186248	0.07900638
230	Vermont	2014	8.4	2.8832214	4.92128639	0.07916669
231	Virginia	2010	9.6	2.35616488	4.75596288	0.66502373
232	Virginia	2011	12.6	2.43609233	5.5402855	0.6710586
233	Virginia	2012	13.6	2.5681688	5.90991504	0.67655247
234	Virginia	2013	9	2.37267932	4.62105117	0.68102912
235	Virginia	2014	7	2.00114671	3.74272988	0.68647204
236	Washington	2010	23.6	7.36056476	13.1798835	0.41445002
237	Washington	2011	21.6	6.15220161	11.5276864	0.42509125
238	Washington	2012	12	6.22084982	8.64003459	0.43363594
239	Washington	2013	16.4	5.47380834	9.47472726	0.44444165
240	Washington	2014	18	5.10445584	9.58541627	0.45095125
241	West Virginia	2010	20.8	2.60695329	7.3637374	0.12733191
242	West Virginia	2011	32.8	2.8531209	9.67379789	0.12764655
243	West Virginia	2012	2	1.8789037	1.93850649	0.12789932
244	West Virginia	2013	0.4	2.37159089	0.97397965	0.13080512
245	West Virginia	2014	12.6	2.16712794	5.22549634	0.13377978
246	Wisconsin	2010	35.6	1.9586223	8.35026669	0.33086015
247	Wisconsin	2011	37.2	2.22566744	9.09916638	0.33663291
248	Wisconsin	2012	26.8	2.80516904	8.67055536	0.34207655
249	Wisconsin	2013	19.2	2.16699946	6.45030151	0.3475026
250	Wisconsin	2014	31.2	2.08964302	8.07445739	0.35070249
251	Wyoming	2010	13.4	2.45948295	5.74082499	0.26080522
252	Wyoming	2011	32.8	1.71707136	7.50466127	0.26337436
253	Wyoming	2012	10.2	1.71707136	4.1849884	0.27662355
254	Wyoming	2013	25.6	1	5.05964426	0.82093343
255	Wyoming	2014	12.6	1	3.54964787	0.29504007

Appendix C: Combined Measure Generator Script

```
tableInput = Open("C:\Users\jshel\Dropbox\Current Projects 2018\Fall 2018 
Courses\Math 599\Combined Measures All States.jmp");


tableOutput = new Table("C:\Users\jshel\Dropbox\Current Projects 2018\Fall 2018 
Courses\Math 599\Combined Measures Analysis.jmp");

tableOutput << NewColumn("State", Character, Nominal);
tableOutput << NewColumn("Year", Numeric, Continuous);
tableOutput << NewColumn("Unemployment Discrepancy", Numeric, Continuous);
tableOutput << NewColumn("Hate Crime Discrepancy", Numeric, Continuous);
tableOutput << NewColumn("Combined Discrepancy", Numeric, Continuous);
tableOutput << NewColumn("Racial Diversity", Numeric, Continuous);

Years = 5;
Races = 3;
RowsWithinState=Years*Races;
NumStates = N Rows(tableInput)/(RowsWithinState);


for (StateItor = 1, StateItor <= NumStates, StateItor++,

tableOutput << Add Rows(Years);

for (YearItor = 1, YearItor <= Years, YearItor++,

OutputRow = (StateItor-1)*Years+YearItor;
InputRow = (StateItor-1)*RowsWithinState+(YearItor-1)*Races+1;

tableOutput:State[OutputRow] = tableInput:State[InputRow];

tableOutput:Year[OutputRow] = tableInput:Year[InputRow];

BlackUnemployment = tableInput:Unemployment[InputRow];
HispanicUnemployment = tableInput:Unemployment[InputRow+1];
WhiteUnemployment = tableInput:Unemployment[InputRow+2];

UnemploymentDiscrepancy = abs(BlackUnemployment - HispanicUnemployment) +
       abs(BlackUnemployment - WhiteUnemployment) +
       abs(HispanicUnemployment - WhiteUnemployment);

tableOutput:Unemployment Discrepancy[OutputRow] = UnemploymentDiscrepancy;

BlackPopulationPercentage = tableInput:"% of Population"[InputRow];
HispanicPopulationPercentage = tableInput:"% of Population"[InputRow+1];
WhitePopulationPercentage=tableInput:"% of Population"[InputRow+2];

BlackHateCrimes = tableInput:Hate Crimes[InputRow];
HispanicHateCrimes =  tableInput:Hate Crimes[InputRow+1];
WhiteHateCrimes = tableInput:Hate Crimes[InputRow+2];
```

```
BlackAdjusted = BlackHateCrimes / BlackPopulationPercentage +1;
HispanicAdjusted = HispanicHateCrimes / HispanicPopulationPercentage +1;
WhiteAdjusted = WhiteHateCrimes/WhitePopulationPercentage + 1;

HateCrimeDiscrepancy = ((BlackAdjusted/HispanicAdjusted)*
       (HispanicAdjusted/WhiteAdjusted)*
       (BlackAdjusted/WhiteAdjusted))^(1/3);
tableOutput:Hate Crime Discrepancy[OutputRow] =
       HateCrimeDiscrepancy;

tableOutput:Combined Discrepancy[OutputRow] =
(HateCrimeDiscrepancy*UnemploymentDiscrepancy)^(1/2);

ThreePopulationPercentage = BlackPopulationPercentage +
HispanicPopulationPercentage+WhitePopulationPercentage;

// Equation 1 From Teachman, 1980.
tableOutput:RacialDiversity[OutputRow] = (3/2)*(1 -
((BlackPopulationPercentage/ThreePopulationPercentage)^2 +

(HispanicPopulationPercentage/ThreePopulationPercentage)^2 +

(WhitePopulationPercentage/ThreePopulationPercentage)^2));

);
);
```

Appendix D: Handout for Correlation Coefficient and Linear Regression (Side 1)

Names:

Date:

Step 1: What does your group think the relationship between race and income in Tucson will be?

Step 2: Is your group going to use white to Hispanic ratio, Hispanic to white ratio, % white, or % nonwhite as your first variable? Construct the variable you want to use in the spreadsheet.

Step 3: Create a scatterplot graph of your variable in Step 2 versus income, and then turn on the correlation coefficient for the graph. What is the correlation coefficient's value? What do you think it means? If it's lower than you expected, why do you think that is? If it's higher, why do you think that is?

Handout Side 2

Step 4: Attempt to draw a line that approximates the data. Discuss how you might tell if this is the best possible line? In what way could you measure how close the data is to the line?

STOP after this question – Discuss as a Whole Class

Step 5: Turn on the display of the equation for the least-squares regression line. How can you test that this is indeed the least-squares regression line? Write out a few sample calculations that would show this.

Step 6: What can you conclude about race vs. income in Tucson from this analysis?

Appendix E: Summative Project for Teaching Innovation

Social Problem Project (Project 3)

In this project, you will be exploring a social problem of your choice.

First, choose a social problem / social movement from the list on the next page of interest to you. Explain why you chose this problem and what you hope to learn.

Part 1: Graph Critique

The goal of this first part of the assignment is to examine at least four sources that contain graphs, which can include newspaper articles, magazine articles, academic journals, infographics, or blog posts. When you look at potential sources, you are looking for sources that contain graphical representations, such as bar graphs, pie charts, histograms, stemplots, or any other type of representation of data that we have studied in this class. (You may also examine a type that we have not studied.)

The Pima College Library website would be a good place to start in looking for resources, and you can also contact a librarian for help from that page. https://www.pima.edu/current-students/library/

Identify the four sources that you consulted, including the name, the author, and the URL if applicable. From these sources, choose two graphs, one that you think is particularly effective and one that you think is particularly ineffective. Include a picture of the graph.

Write at least two paragraphs for each graph. In the first paragraph, explain what type of graph it is and compare it to similar graphs in the textbook. Explain the purpose of the graph; what is it trying to explain to the reader and what is the target audience of the graph. Discuss whether the graph meets the needs of that audience.

In the second paragraph, critique the graph in terms of its layout, content, and clarity. What features of the graph make it clear to the reader? What features might be misleading? Consider type of graph, labels on the axes, scale of the axes, use of color, missing information, and size of the features of the graph. How might you fix the graph to better present the information to the reader?

Part 2: Researching Your Issue

Imagine you are conducting a study on your social problem. Make a list of different variables (minimum of 3) that you might collect data about to research your problem. Write one paragraph addressing the following: Describe a way in which you might collect your data. Are your variables quantitative or categorical? Which variables do you think will be linked? How strong of a relationship do you think there is?

Read the credible source guide from Spokane Falls Community College:

https://tinyurl.com/CredibleSourceGuide

and find one credible source that explores the connection between two of your variables. Write at least two paragraphs answering the following questions: How do they define the variables? Did they find any relationship between them? How did this compare to your conjectures? How does this help you better understanding the graphs from part 1?

Please submit this assignment to the Project 3 assignment dropbox on D2L.

Grading:

Grading out of 10 points:

Explanation of Choice of Problem (2 pts)

2 Problem chosen from list, explained in at least two sentences

1 Problem chosen but not explained

0 No problem chosen

Choice of Graphs (2 pts)

2 Four sources consulted, two graphs are chosen, graphs are included with sources identified. Graphs reflect the goals of having one effective and one ineffective graph.

1.5 Two graphs are included, but less than fur sources were consulted, or there is not one graph of each type.

1 Only one graph is included

0 No graphs included.

Critiques of Graphs (2 pts)

2 Type, purpose, audience, and features are clearly identified and critiqued. Each graph has a minimum of two paragraphs. For the ineffective graph, ways of improving it are identified.

1 Missing two to three of the required characteristics. Response is a single paragraph or is a disjoint set of sentences.

0 None of required characteristics submitted.

(Continued in next column)

Issue Research (4 pts)

4 All three of the following satisfied: One paragraph identifying at least 3 variables and making predictions included. Article identified meets credible source criteria. Two paragraphs analyzing the article included.

3 Two of the above criteria satisfied, or all three included but not of sufficient length

2 One of the above criteria satisfied

1 Issue Research Included but does not meet any criteria

0 No issue research section included.

List of Social Problems and Social Movements

Academic Freedom

Adoption

Advertising, children's

Affirmative Action

Ageism

AIDS/HIV

Air Pollution

Airline Issues

Alcohol Abuse

Animal rights

Anti-Muslim Discrimination and Violence

Anti-Semitism

Arson

Arts Funding and Censorship

At Risk Students: Higher Education

Attention Deficit-Hyperactivity Disorder

Autism

Automobile and Highway Safety

Bi-lingualism

Birth Control

Campaign Finance Reform

Cancer

Capital Punishment

Census Issues

Cheating, academic

Child Abuse and Molestation

Child Labor

Chronic Fatigue Syndrome

Church-State Separation

Civil Liberties

Civil Rights

Coastal Pollution and Wetlands Protection

College Sports

Computer Crime, Hacking

Consumer Debt and Bankruptcy

Corporal Punishment

Corporate Crime

Crime

Criminal Rights

Cults and Alternative Religions

Defense Spending and Preparedness

Deforestation and Logging

Disability Rights

Divorce and Child Support

Domestic Violence

Downsizing, corporate

Drought and aquifer depletion

Drug Abuse

Drugs, War on

Eating Disorders

Energy Dependency

Environmental Justice

Environmentally-induced Illness

Euthanasia

Evolution Education

Extinction and Species Loss: Biota Invasion and Habitat Destruction

Farm crisis

Fat Discrimination*

Food and Drug Safety

Foster Care

Gambling

Gangs

Gay, Lesbian, Bisexual, Trans Rights*

Genetic Engineering

Gentrification

Global Warming

Gun violence and gun control

Hate Crimes

Hate Internet and Radio

Hate Speech

Health Care Reform

Heart Disease

Homelessness

Housing costs

Human experimentation

Identity Theft

Immigrants’ Rights*

Indoor Pollution

Infectious Diseaseand Epidemics

Infrastructure Deterioration

Intellectual Property Rights

Journalistic Ethics

Judicial Reform

Juvenile Justice

Legal Services for the Poor

Literacy

Mandatory Sentencing

Marijuana

Mass Transit

Media Bias

Media Consolidation

Media Sex and Violence

Medical Malpractice

Medicare and Medicaid Reform

Medicine, alternative

Mental Illness

Migrant Workers

Militia Movement

Minimum and Living Wages

Money Laundering

N(ot) I(n) M(y) B(ackyard) Y(ard) Issue

Native Americans and Government Policy

Natural Disasters and Disaster Relief

Needle Exchange Programs

Noise Pollution

Nuclear Power and Waste

Nuclear Weapons

Occupational Safety and Health

Organ and Tissue Transplants

Organic Foods

Organized Crime

Plagiarism

Police Abuse and Corruption

Pornography

Poverty and Wealth

Prison Reform and Prisoner Rights

Privacy

Prostitution

Public Opinion Polling

Racial Profiling

Rape

Recycling and Conservation

Red-lining and loan discrimination

Reproductive Rights and Technology

Rioting

School Standards and Testing

School Violence

School Vouchers and Privatization

Scientific Research Ethics

Secrecy, Governmental

Sex Education

Sexual Harassment

Single Parenting

Social Security Reform

Space Exploration, costs and benefits

Special Education

Stem Cell Research

Stress

Student Rights

Suicide

Superstores v. Main Street

Sweatshops

Tax Reform

Term Limits

Terrorism, Domestic

Terrorism, Foreign

Terrorism, War on

Tobacco and tobacco-related health issues

Tort Reform

Toxic Waste

Traffic Congestion

Unemployment

Unions

Urban Sprawl

Veterans' Issues

Voluntarism and Volunteering

Voting Issues

Waste Disposal

Water Pollution