

A Glimpse on Federalizing Public Education

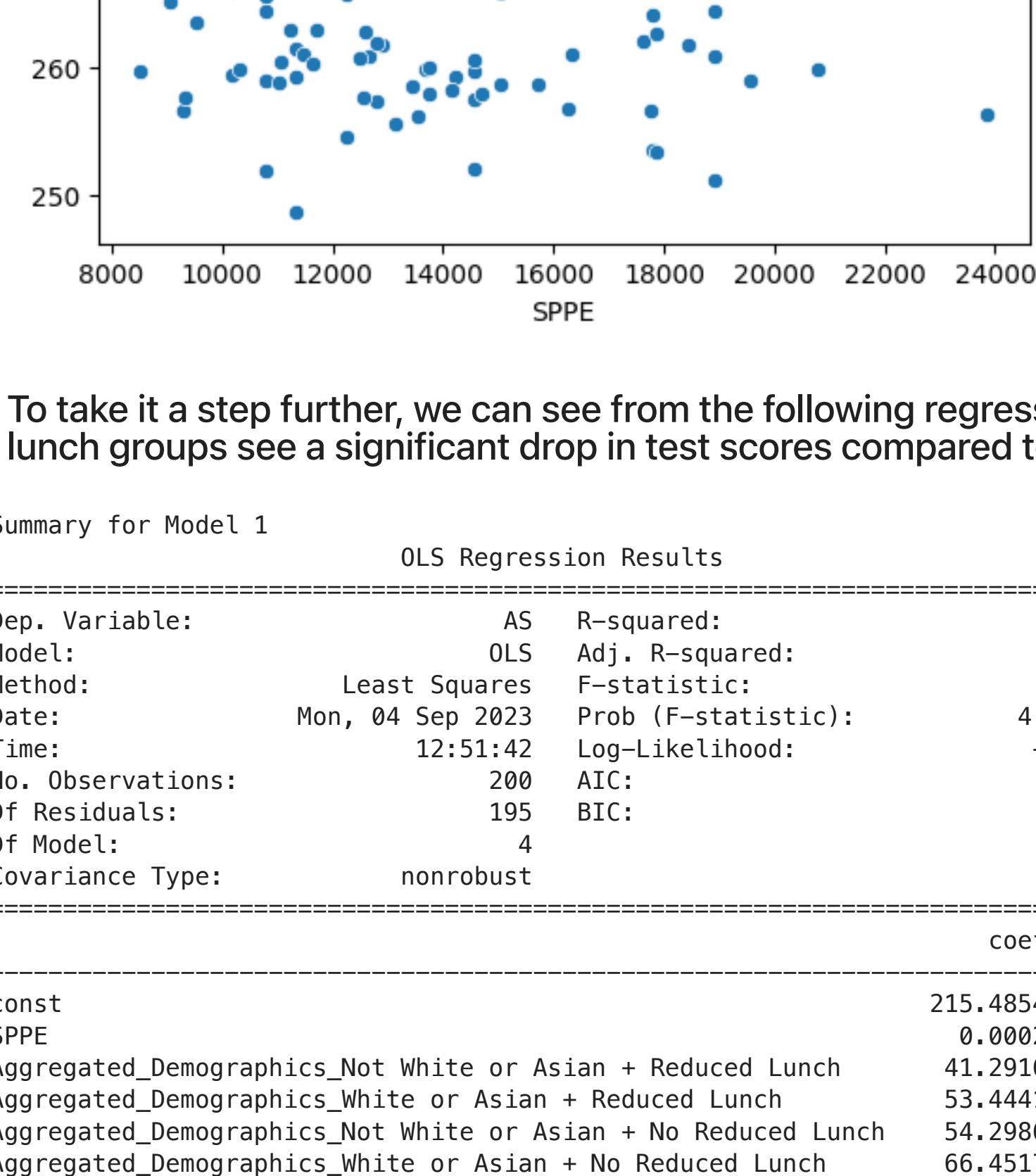
This is meant as a hypothetical test, based solely upon theory and existing data. The political ramifications of such are not discussed, as it provides more of a glimpse into a potential alternative theoretical pathway to addressing education rather than a realistic possibility of being implemented. Various Python packages are used, and you will find integrated Tableau visualizations as well as an exported SQL database created to host the code.

Created by Kolbe Alexandre Dumas with assistance of ChatGPT 4

The data is sourced from the NAEP, BEA, and NCES, and contains the following: data on 8th grade achievement scores by state (denoted by variable AS), broken into demographics of Ethnicity, Subject (math and reading), and Reduced Lunch status. It also contains data on demographic Per-Pupil Expenditure (PPE) by state, and state Regional Price Parities (RPP) data to be used to standardize PPE into a value that can be compared across different costs of living - this variable is SPPE. The demographic data has been aggregated into four categories: Not White or Asian and Reduced Lunch, Not White or Asian and No Reduced Lunch, White or Asian and Reduced Lunch, and White or No Reduced Lunch.

/var/kolbedumas/miniconda3/lib/python3.10/site-packages/openspyxl/worksheet/header_footer.py:48: UserWarning: Cannot parse header or footer so it will be ignored
warnings.warn("Cannot parse header or footer so it will be ignored")

The following is an initial scatter plot of SPPE vs AS, as the graph shows, there does not seem to be any correlation between a state's spending on education and achievement scores.



To take it a step further, we can see from the following regression analysis that SPPE is not statistically significant; however, we see that the demographic groups are. Not White or Asian + Reduced Lunch groups see a significant drop in test scores compared to White or Asian + No Reduced Lunch; a difference in roughly 25 points.

Summary for Model 1

OLS Regression Results

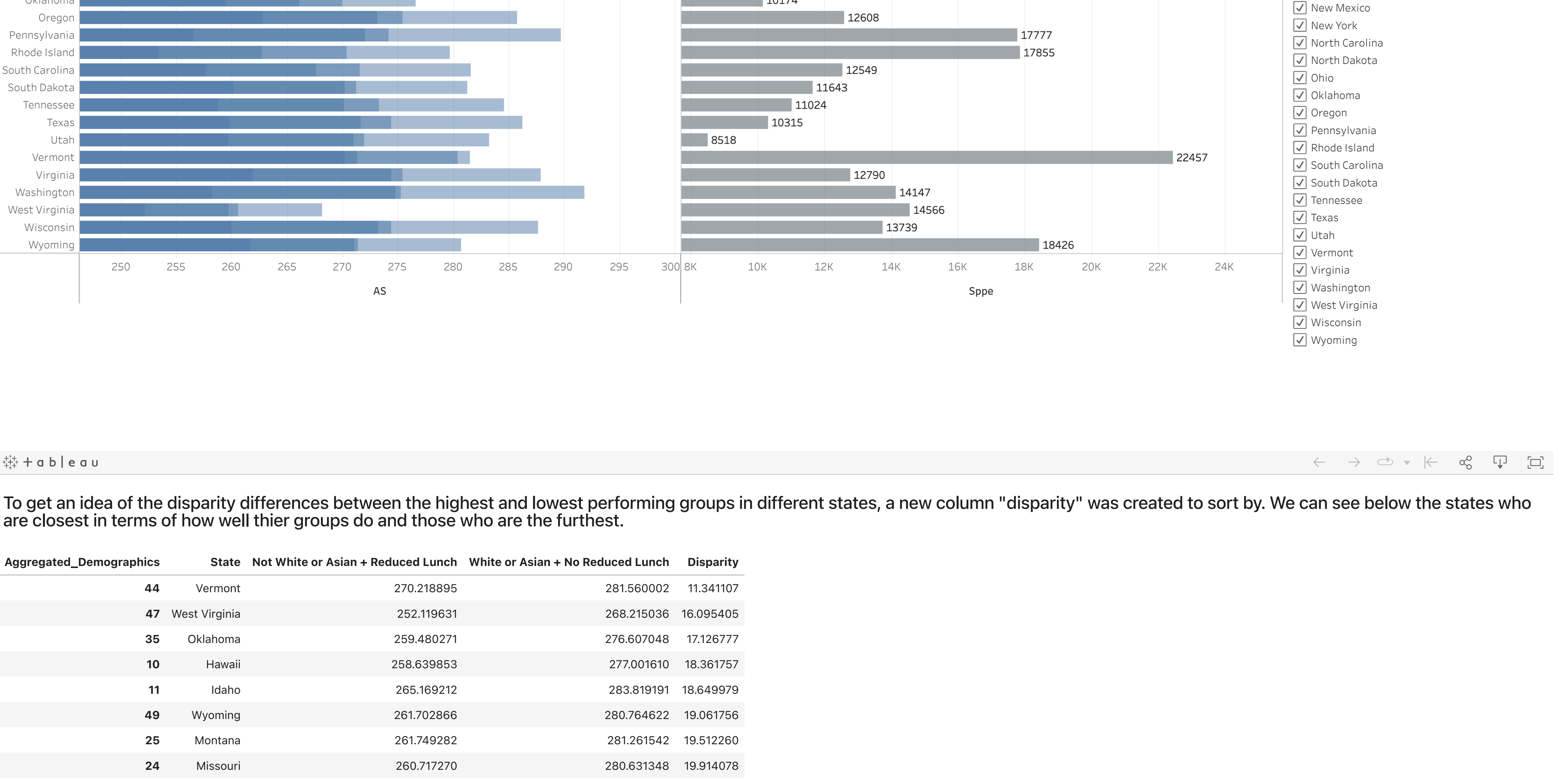
Dep. Variable:	AS	R-squared:	0.791
Model:	OLS	Adj. R-squared:	0.776
Method:	Least Squares	F-statistic:	173.6
Date:	Mon, 04 Sep 2023	Prob (F-statistic):	4.28e-63
Time:	12:51:42	Log-Likelihood:	-594.35
No. Observations:	200	AIC:	1199.
DF Residuals:	195	BIC:	1215.
DF Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	215.4854	1.112	193.763	0.000	213.292	217.679
SPPE	0.0002	9.05e-05	1.566	0.119	-3.92e-05	0.000
Aggregated_Demographics_Not White or Asian + Reduced Lunch	41.2910	0.649	63.659	0.000	40.012	42.570
Aggregated_Demographics_White or Asian + Reduced Lunch	53.4441	0.649	82.396	0.000	52.165	54.723
Aggregated_Demographics_Not White or Asian + No Reduced Lunch	54.2986	0.649	83.713	0.000	53.019	55.578
Aggregated_Demographics_White or Asian + No Reduced Lunch	66.4517	0.649	102.449	0.000	65.172	67.731

Omnibus: 5.560 Durbin-Watson: 1.038
Prob(Omnibus): 0.862 Jarque-Bera (JB): 1.038
Skew: -0.385 Prob(JB): 0.8058
Kurtosis: 3.530 Cond. No. 7.98e+19

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 6.66e-30. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

Below are three visualizations crafted in Tableau that can be filtered through to see specific data on state AS scores for the various demographics as well as the state's SPPE for reference.



To get an idea of the disparity differences between the highest and lowest performing groups in different states, a new column "disparity" was created to sort by. We can see below the states who are closest in terms of how well their groups do and those who are the furthest.

Out [94]:

Aggregated_Demographics	State	Not White or Asian + Reduced Lunch	White or Asian + No Reduced Lunch	Disparity
44	Vermont	270.218895	281.560002	11.341107
47	West Virginia	252.119631	268.215036	16.095405
35	Oklahoma	259.480271	276.607048	17.126777
10	Hawaii	258.639853	277.001610	18.361767
11	Idaho	265.169212	283.819191	18.649979
49	Wyoming	261.702866	280.764622	19.061756
25	Montana	261.749282	281.261542	19.512260
24	Missouri	260.717270	280.631348	19.914078
15	Kansas	260.846375	281.362538	20.516163
13	Indiana	263.008043	283.930549	20.922505

Out [95]:

Aggregated_Demographics	State	Not White or Asian + Reduced Lunch	White or Asian + No Reduced Lunch	Disparity
31	New York	256.393260	285.144028	28.750768
20	Massachusetts	266.474012	296.474094	30.000082
2	Arizona	256.557819	287.659526	31.101707
4	California	257.309570	288.859906	31.550336
34	Ohio	259.319183	291.401303	32.082120
19	Maryland	258.616407	291.002860	32.386453
37	Pennsylvania	256.564104	289.718137	33.154034
46	Washington	258.228494	291.892710	33.664212
6	Connecticut	259.900224	294.174783	34.274569
29	New Jersey	259.047161	298.082595	39.035434

From the data we have, we can see there are essentially a few key factors: some states are very good in terms of overall scoring, however, they lack when it comes to narrowing the achievement gap as the disparity between the top performing groups and the bottom performing groups is large. There are also states who do fairly well at minimizing the achievement gap, but their overall scores lack. The idea is the following: if education were to be federalized, and thorough research was done on the top 5 states in each of these categories (lowest disparity + highest average AS score), could you combine the approaches to education these states take into one singular approach that combines them? This model attempts to do so, giving more weight to reducing the achievement score (0.7 to 0.3).

	AS	Projected_AS	Reduced_Disparity_AS
count	160.000000	160.000000	160.000000
mean	271.057189	278.074690	268.229545
std	9.806241	3.558134	9.825066
min	248.780559	267.428058	246.656044
25%	262.780043	276.542893	261.059433
50%	271.529317	278.337541	268.053634
75%	276.473223	280.983220	273.934603
max	291.892710	282.986949	285.845184

Current Scores Descriptive Statistics:

count	160.000000
mean	271.057189
std	9.806241
min	248.780559
25%	262.780043
50%	271.529317
75%	276.473223
max	291.892710

Name: AS, dtype: float64

Composite Scores Descriptive Statistics:

count	160.000000
mean	275.121146
std	4.438226
min	261.194414
25%	272.261057
50%	275.383238
75%	278.395199
max	283.417952

Name: Composite_Score, dtype: float64

Summary for the Filtered Model

OLS Regression Results

Dep. Variable:	AS	R-squared:	0.830
Model:	OLS	Adj. R-squared:	0.826
Method:	Least Squares	F-statistic:	189.9
Date:	Mon, 04 Sep 2023	Prob (F-statistic):	1.19e-58
Time:	12:51:42	Log-Likelihood:	-449.82
No. Observations:	160	AIC:	909.6
DF Residuals:	155	BIC:	925.0
DF Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	217.7134	1.077	202.094	0.000	215.585	219.841
SPPE	-8.018e-05	9.66e-05	-0.830	0.408	-0.000	0.000
Aggregated_Demographics_Not White or Asian + Reduced Lunch	41.8448	0.621	67.348	0.000	40.617	43.072
Aggregated_Demographics_White or Asian + Reduced Lunch	53.9417	0.621	86.817	0.000	52.714	55.169
Aggregated_Demographics_Not White or Asian + No Reduced Lunch	54.9149	0.621	88.384	0.000	53.688	56.142
Aggregated_Demographics_White or Asian + No Reduced Lunch	67.0119	0.621	107.853	0.000	65.785	68.239

Omnibus: 4.948 Durbin-Watson: 1.035
Prob(Omnibus): 0.084 Jarque-Bera (JB): 4.812
Skew: 0.294 Prob(JB): 0.0902
Kurtosis: 3.612 Cond. No. 7.24e+19

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 5.93e-30. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

The model shows what the numbers could look like in this theoretical situation; we see average scores raise, and the disparity lowers significantly compared to what it was before. While top scores might come down a bit, this would be a necessary price to pay. Below are visualizations of the current numbers and the projected numbers. A random forest was also ran to get a potential SPPE value that would be standard.

Out [98]: Text(0, 0.5, 'Scores')



Predictions:
0 11302.051174
1 11392.482790
2 12004.317888
3 11332.036970
4 11302.051174
Name: Aggregate_SPPE, dtype: float64