Milestone 7

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Abstract

This is an extension of Jessica Trounstine's "Segregation and Inequality in Public Goods" (2016). I was able to replicate the main results of Trounstine's paper in R to suggest that racial segregation contributes to political polarization and decreased spending on public goods. Additionally, I extend the analysis by imputing missing data and rerunning Trounstine's original model as a robustness check.

Introduction

This is my pdf document. Please refer to the Github repository of my final project for further information.[1]. You can also access all of the original replication materials made available by Trounstine on Harvard Dataverse here. I make use of Trounstine (2016), Pencharz and Ball (2003), Xie (2020), Wickham (2019), and Xie (2015).

Summary of Trounstine (2016)

Trounstine's *Segregation and Inequality in Public Goods* attempts to explain differences in public goods provision and political polarization through a racial lens by examining the relationships between polarization, goods provision, and segregation. Trounstine measures segregation with Theil's H index, which measures the degree to which the diversity of a neighborhood differs from the diversity of the entire city. The main finding of the paper is that segregation, not simply diversity or political views, is an important determinant of both political polarization and spending on public goods. In general, segregation leads to the coincidence of racial and spatial political cleavages, which can make compromise on taxation and public spending difficult and tends to generally drive down the rate of spending on public goods. Because minorities are much more likely to live in racially segregated areas than whites, this suggests that public goods are also segregated across racial lines.

Literature Review

This is my literature review. Sources will be added when a more thorough job is done for milestone #8.

In the United States, residential segregation across racial lines remains a deeply entrenched problem in our society.

[1]All sources, analysis, and further information are available on my Github repository for this project

Neighborhood racial isolation has been associated with racial intolerance and increased political competition. Those who live in homogenous neighborhoods are also more likely to believe in negative stereotypes about out-groups.

On the city level, diversity is associated with increased racial tension, lower levels of cooperation, intolerance, and lower spending on public goods.

A combination of homogenous neighborhoods within a diverse city leads to severe segregation and high degrees of racial tension.

Racial segregation has been associated with partisan political divides and a lack of cooperation across groups on city-wide policy.

Replication

Table 1 was able to be replicated exactly. The replication for Table 2 was close, but not exact, as were the replications for Table 3 and 4, which combined replicated Table 3 in the main paper. However, the implications of the main results are essentially the same for all of these regressions. The IV regression was able to be replicated exactly and the results presented in Tables 5 and 6 reconstruct the results from Table 5 in the original paper. So far, I have not been able to successfully recreate the marginal effects; however, I am working to figure out what the problem is. I believe that with a little bit more time I will be able to successfully recreate all of the results given my success in Table 1 and Tables 5 and 6.

As for the paper's Appendix Tables, I was able to successfully recreate Tables A1 and A2. I have not yet been able to sucessfully recreate Table A3 in Stata because I am having difficulty in figuring out why I have fewer observations and also how they calculated some of their statistics, as it seems that they filter for some conditions only for some rows, which I have yet to figure out how to do in R. I did not attempt to recreate Table A4 due to time constraints and also because it seemed extraneous.

Extension Ideas

There are a variety of ways that I could build upon this analysis. Because I have not narrowed it down to one yet, I will use this as an opportunity to propose a few ideas.

How well does this theory apply to more recent elections, and can we use new data to test it? For example, I could try to hunt down some more recent election data and use some sort of prediction funciton to see how well the model predicts the actual results. However, this could be quite difficult if the data is too messy or difficult to obtain (or even non-existent).

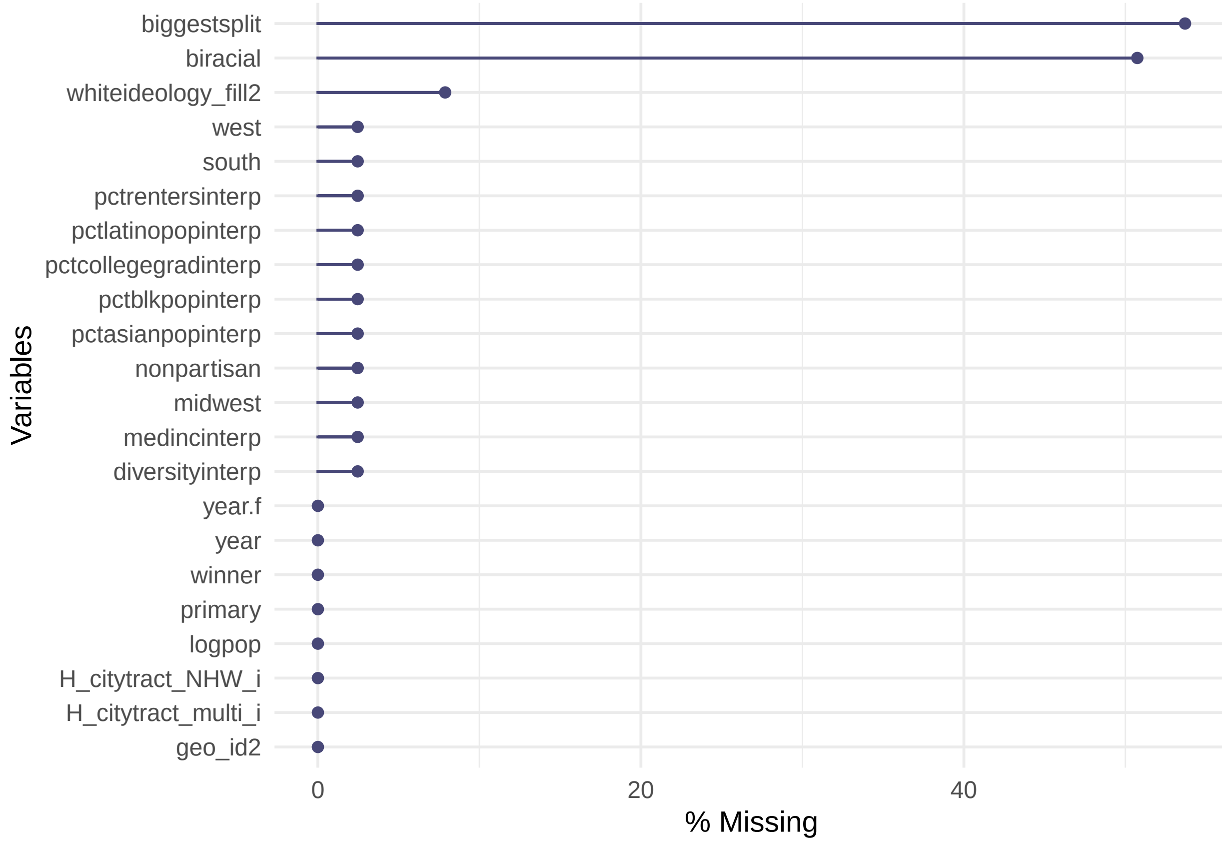
Another idea could be to redo the results but using the dissimilarity index, the most common measure of segregation, which Trounstine, perhaps controversially, chooses not to use in her analysis in favor of Theil's entropy score. It could be interesting to see whether her results hold up against this sort of robustness check.

Another interesting thing to do would be to find a city that has recently become less segregated and see if political polarization has decreased and public goods provision has increased.

Finally, another approach to put to practice some more of the skills we've learned in this class would be to try and adpot a Bayesian framework to some of Trounstine's analyses.

Extension 1

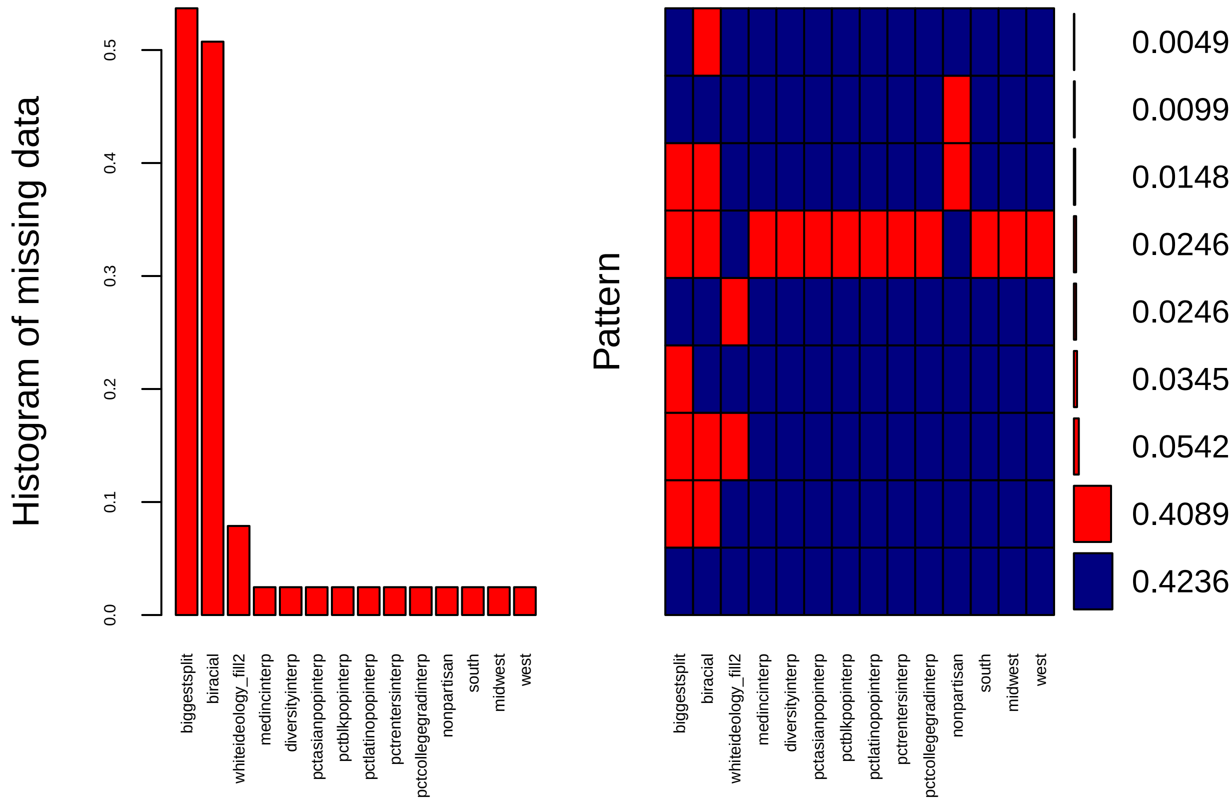
One aspect of Trounstine's paper with room for improvement is that there is a large amount of missing data in her datasets upon which she bases her analyses. Using R's mice package (add citation), we can perform multiple imputation. By performing imputation multiple times, this helps account for the uncertainty inherent in the individual imputations. Before performing the multiple imputations, we will first look at the missing data to see if there are any patterns.



The above plot reveals that biggestsplit and biracial are the two variables with by far the largest percentage of missing values. Both of these are missing approximately 50% of their observations. Since biggestsplit is the dependent variable in our analysis with this dataset, this is an important fact.

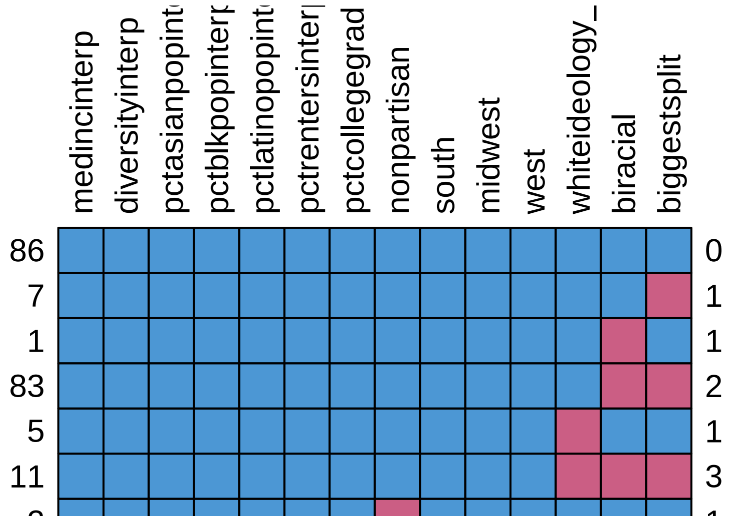
```
rp_aggr <- rp_impute %>%
   select("medincinterp",
             "biggestsplit", "diversityinterp",
             "pctasianpopinterp", "pctblkpopinterp", "pctlatinopopinterp",
             "pctrentersinterp", "pctcollegegradinterp", "biracial", "nonpartisan",
               "south", "midwest", "west", "whiteideology_fill2")

aggr_plot <- aggr(rp_aggr, bars = TRUE, col=c('navyblue','red'), numbers=TRUE, sortVars=TRUE, cex.axis=
```




```
 Variables sorted by number of missings:
             Variable      Count
         biggestsplit 0.53694581
             biracial 0.50738916
  whiteideology_fill2 0.07881773
         medincinterp 0.02463054
      diversityinterp 0.02463054
    pctasianpopinterp 0.02463054
      pctblkpopinterp 0.02463054
   pctlatinopopinterp 0.02463054
     pctrentersinterp 0.02463054
 pctcollegegradinterp 0.02463054
          nonpartisan 0.02463054
                south 0.02463054
              midwest 0.02463054
                 west 0.02463054
```

```r
md.pattern(rp_aggr, rotate.names = TRUE)
```



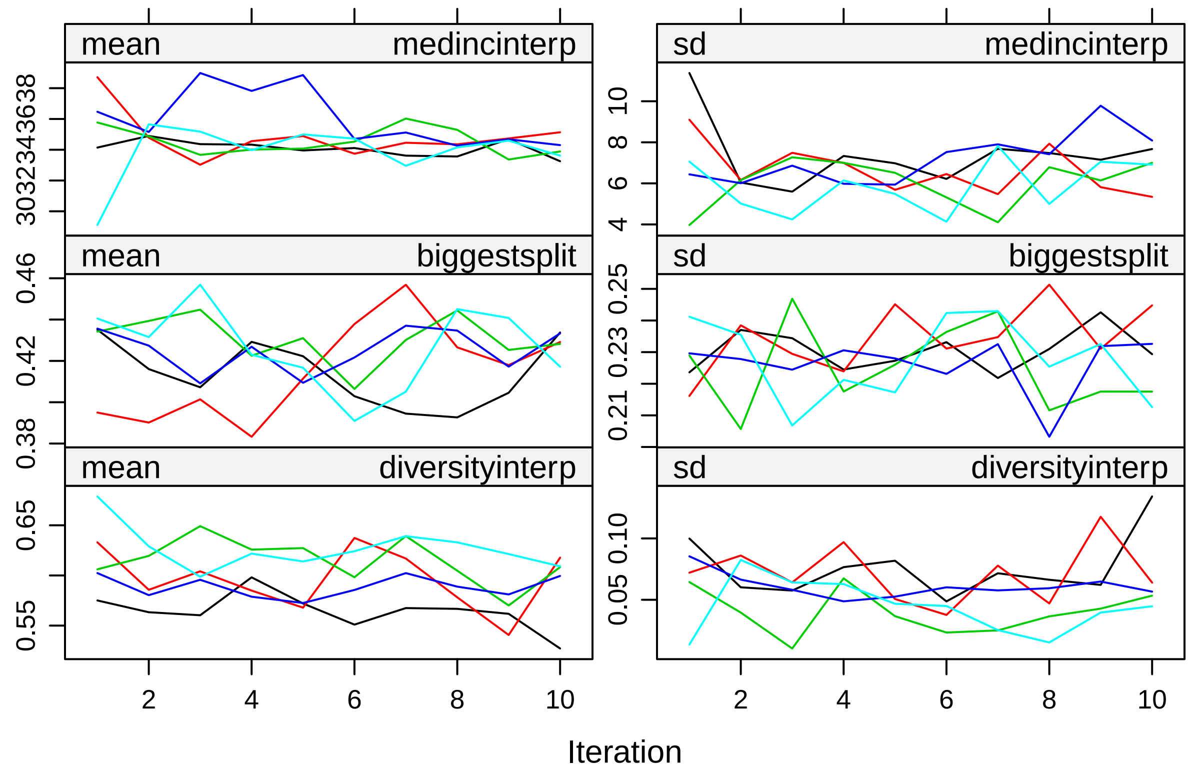

```
   medincinterp diversityinterp pctasianpopinterp pctblkpopinterp
86            1               1                 1               1
7             1               1                 1               1
1             1               1                 1               1
83            1               1                 1               1
5             1               1                 1               1
11            1               1                 1               1
2             1               1                 1               1
3             1               1                 1               1
5             0               0                 0               0
              5               5                 5               5
   pctlatinopopinterp pctrentersinterp pctcollegegradinterp nonpartisan south
86                  1                1                    1           1     1
7                   1                1                    1           1     1
1                   1                1                    1           1     1
83                  1                1                    1           1     1
5                   1                1                    1           1     1
11                  1                1                    1           1     1
2                   1                1                    1           0     1
3                   1                1                    1           0     1
5                   0                0                    0           1     0
                    5                5                    5           5     5
   midwest west whiteideology_fill2 biracial biggestsplit
86       1    1                   1        1            1   0
7        1    1                   1        1            0   1
1        1    1                   1        0            1   1
83       1    1                   1        0            0   2
5        1    1                   0        1            1   1
11       1    1                   0        0            0   3
2        1    1                   1        1            1   1
3        1    1                   1        0            0   3
5        0    0                   1        0            0  12
         5    5                  16      103          109 283
```

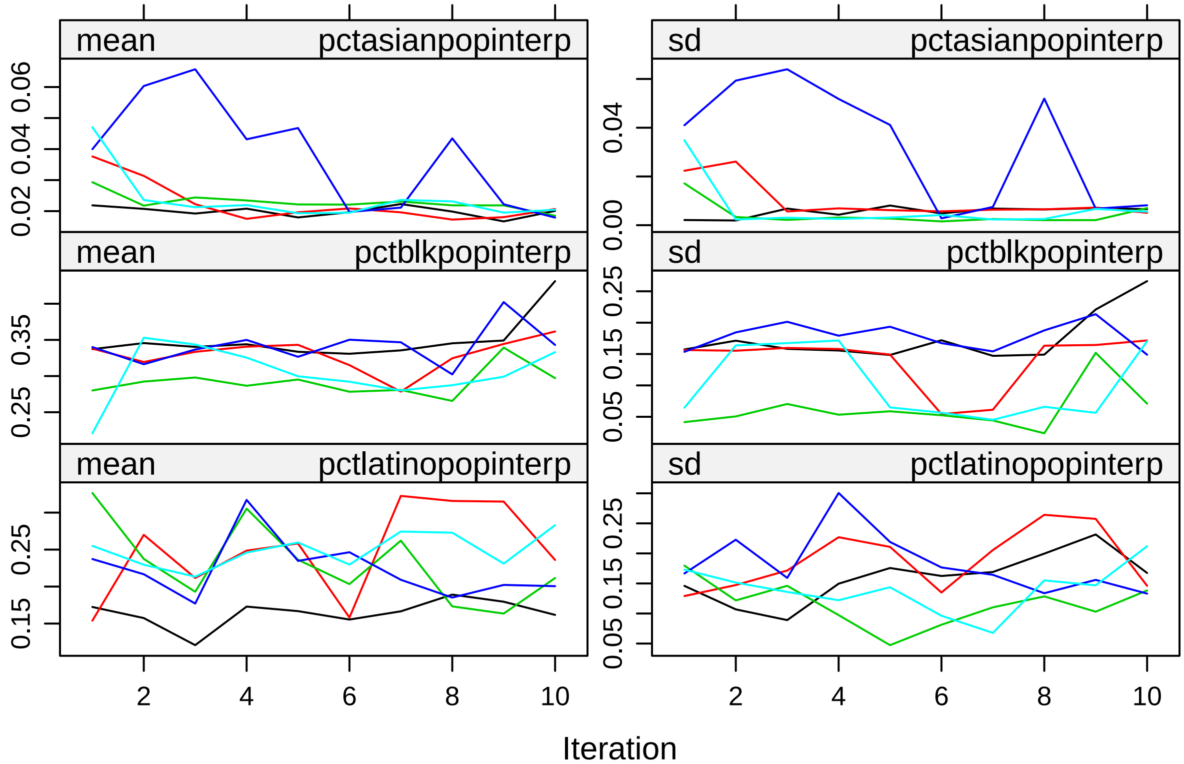
```
# this plot tells us that 42% of the data are not missing anything
```

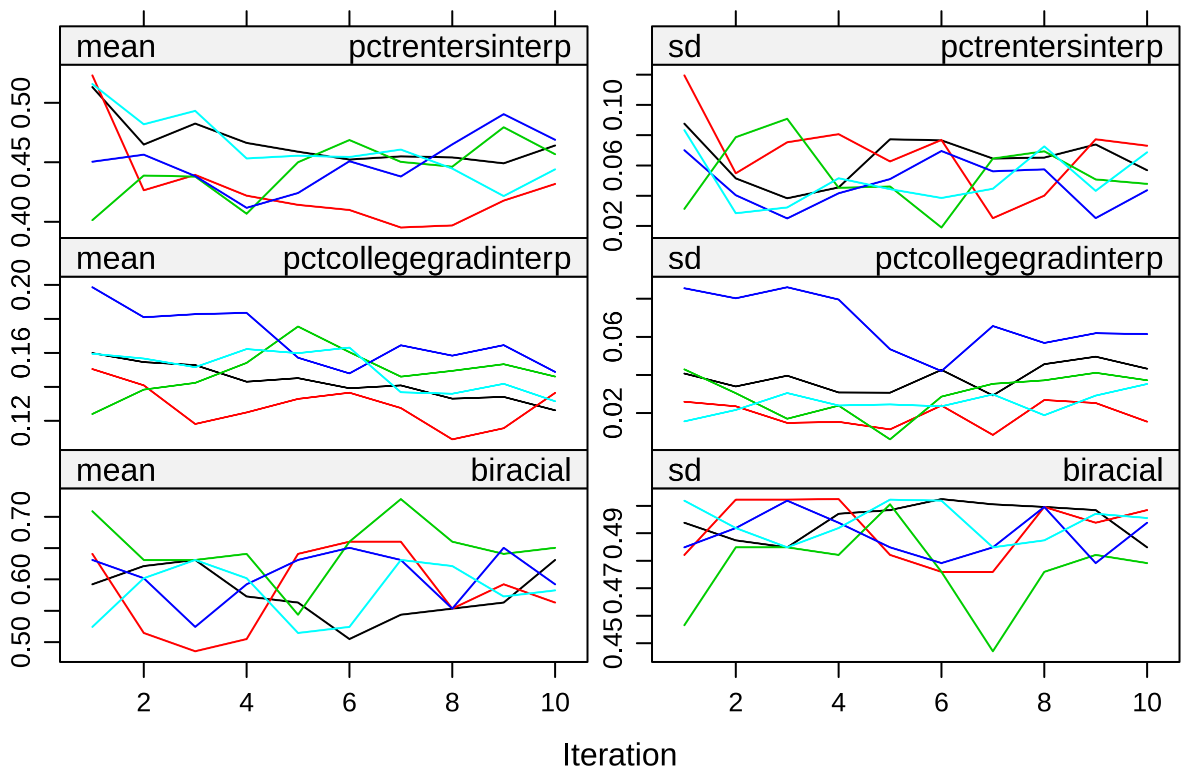
To better understand any potential patterns in missing data, we then plotted the pattern of missingness for only those variables missing values. From the plot on the right, we can see that approximately 42% of observations are complete. There seem to be a correspondence between missing a value for biggest split and missing biracial. There also seem to be about 2% of values for wich most of the variables are missing. However, most observations are not missing more than 2-3 values.

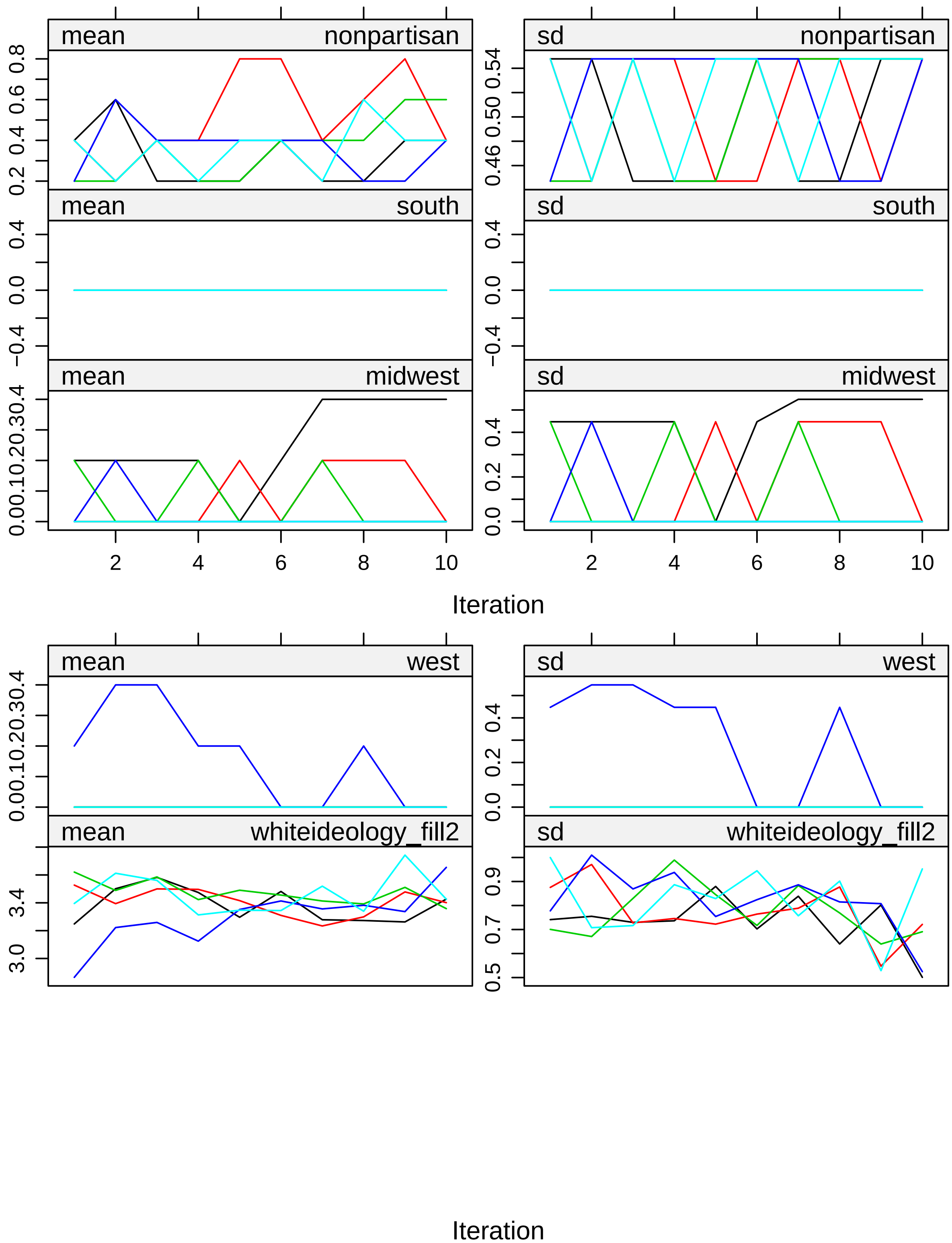
Finding no clear patterns in the missing data, I next performed mutliple imputations (with 10 iterations) on the dataset. A non-stochastic imputation method, Classification and Regression Trees (CART), was used instead of the default because of an error with matrix inversion caused by the data. Before examining the results of Trounstine's model using the imputed data, I first run some diagnostic tests of the imputation results to make sure that everything is running as expected.

First, I check the convergence of the algorithm used within mice() for each of the variables. For the most part, the fits intertwine and do not exhibit any trends at later iterations, as desired. There are some issues with the results for some of the variables with very few missing values (such as West and South), which makes sense as we would expect the mean to be less reliable due to the law of large numbers, and convergence is more difficult. Nevertheless, since there are so few of these values in the actual dataset, this is not a major concern.

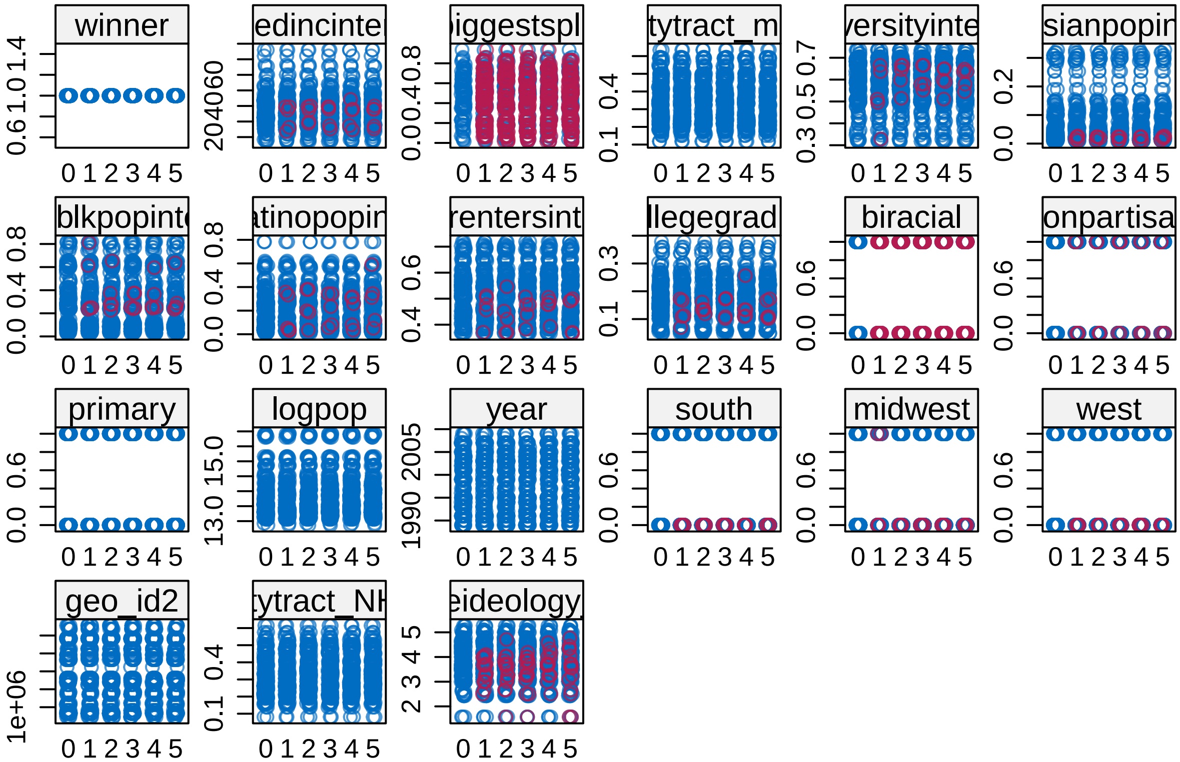


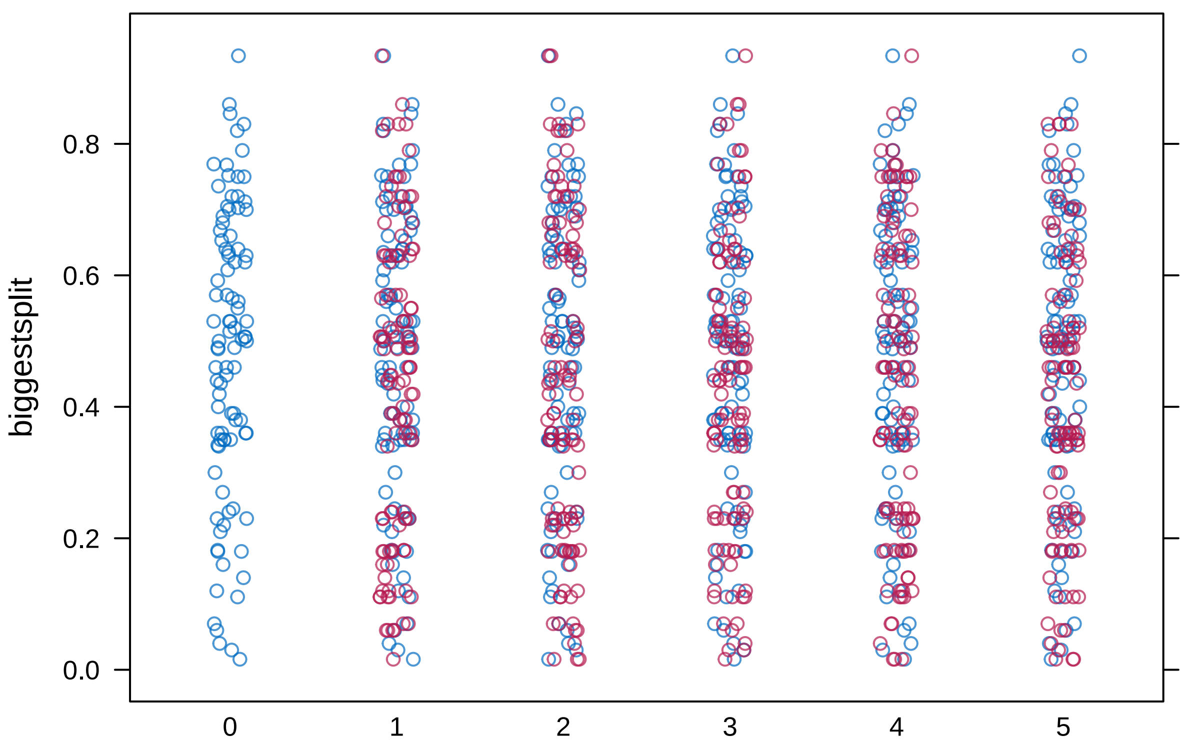

mean pctasianpopinterp
sd pctasianpopinterp
mean pctblkpopinterp
sd pctblkpopinterp
mean pctlatinopopinterp
sd pctlatinopopinterp
Iteration


mean pctrentersinterp
sd pctrentersinterp
mean pctcollegegradinterp
sd pctcollegegradinterp
mean biracial
sd biracial
Iteration

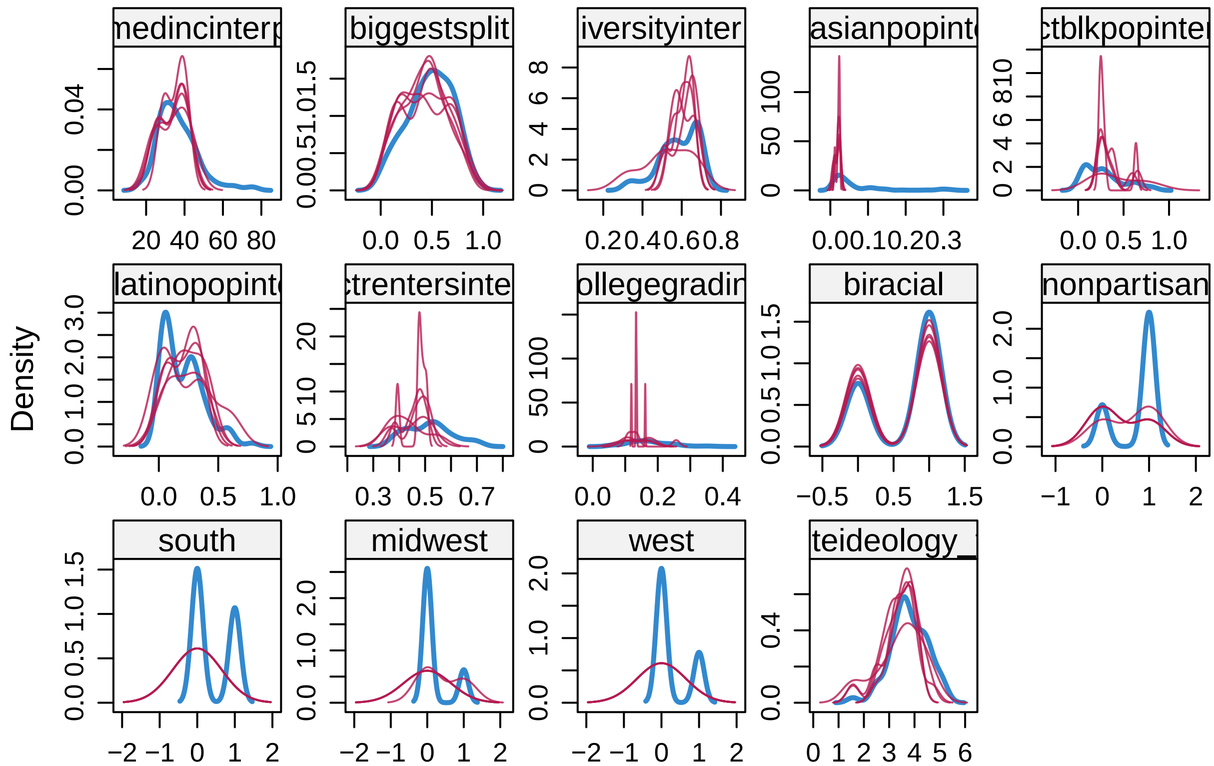


We can also check the imputed values against the original values using stripplot(). Each column in each subplot represents a separate iteration. The magenta points represent the imputed data. The values of the variable in questions are along the y axis. We expect the spread of the data to be similar if the imputations were done well. If the data were missing completely at random, then the imputed data should have the same distribution as the original data. In particular, we want to be sure that the imputations are within a plausible range of the data. This is the case for all of our imputed variables, and there does not seem to be cause for alarm from these results.





Finally, we can also look at the density plots for each variable's actual data and for their imputed data from each of the iterations, which are represented in magenta. Overall, the density plots align quite well for the variables with the most missing data, biracial and biggestsplit, and relatively well for most of the other variables with missing data. Again, the fit is less good for variables with fewer missing data points.



While the imputations are not perfect, there do not seem to be any major problems so far. Thus, we can now proceed with our analysis. We fit each of our ten imputed datasets to Trounstine's 3 models using this data and then pool the results for each. The results are as follows:

Extension 1 Racial Polarization Table

Regression 1

	term	estimate	std.error	p.value
1	(Intercept)	0.021289728	0.428314633	9.609281e-01
2	H_citytract_multi_i	0.424903753	0.386881542	2.974014e-01
3	diversityinterp	0.157450011	0.336414986	6.466862e-01
4	pctasianpopinterp	-0.073034854	0.444854156	8.720015e-01
5	pctblkpopinterp	0.178639425	0.221495595	4.373528e-01
6	pctlatinopopinterp	0.164075368	0.214956001	4.610619e-01
7	medincinterp	-0.001305195	0.003899519	7.399154e-01
8	pctrentersinterp	-0.505540820	0.245655070	4.293737e-02
9	pctcollegegradinterp	0.492826278	0.480209115	3.137296e-01
10	biracial	0.222204013	0.028445949	1.156828e-08
11	nonpartisan	-0.084784453	0.063719326	2.135170e-01
12	primary	-0.068569601	0.022538375	2.947573e-03
13	logpop	0.021215866	0.030728917	4.943477e-01

The results of the model with the new dataset are slightly different in comparison to the original results from Trounstine (2016). With the imputed data, we now have a total of 203 observations in our model as compared to the original model, which had only 91 observations. Interestingly, while the sign of the coefficient on the main variable of interest, the Theil's H segregation index is the same and the standard error has decreased slightly, the result has become statisically insignificant and the 95% confidence interval contains zero. Thus while these results still suggest that segregation may be associated with increased political polarization, they confer a lesser degree of certainty than Trounstine's original analysis. The coefficients for pctblkpopinterp, pctlatinopopinterp, and medincinterp have also switched signs, and all coefficients except indicators for a biracial and primary election are also statistically insignificant, as was the case in the original analysis. In general, the standard error on the coefficients has decreased slightly.

In the second and third regressions, the results are similar in comparison to the unimputed data to the first. Standard errors have reduced slightly. The main coefficient on segregation index has decreased in magnitude, although in these specifications, it remains statistically significant. The other coefficients except for biracial and primary are insignificant, and the coefficients on percent Asian, Black, and Latino have all switched signs.

Regression 2

```
                     term     estimate   std.error      p.value
1             (Intercept) -0.028021685 0.429391912 9.487522e-01
2         H_citytract_NHW_i  0.503812393 0.274260488 8.465817e-02
3         diversityinterp  0.128086138 0.278403460 6.497486e-01
4      pctasianpopinterp  0.096327684 0.448519030 8.328082e-01
5        pctblkpopinterp  0.200753636 0.176609378 2.745499e-01
6     pctlatinopopinterp  0.208709231 0.217173836 3.581982e-01
7            medincinterp -0.002197686 0.003739137 5.598618e-01
8       pctrentersinterp -0.590022278 0.239549408 1.527298e-02
9   pctcollegegradinterp  0.646050477 0.466141649 1.746476e-01
10               biracial  0.220179445 0.028209600 1.265350e-08
11            nonpartisan -0.073206205 0.063241354 2.746007e-01
12                primary -0.067852253 0.022558381 3.347131e-03
13                 logpop  0.024484858 0.030505455 4.274870e-01
```

Regression 3

```
                     term     estimate  std.error      p.value
1             (Intercept) -0.057209577 0.42854984 8.954317e-01
2         H_citytract_NHW_i  0.476314380 0.27242266 9.894688e-02
3         diversityinterp  0.167218557 0.27603962 5.502128e-01
4      pctasianpopinterp  0.120181421 0.45108654 7.936525e-01
5        pctblkpopinterp  0.223218134 0.17199570 2.129575e-01
6     pctlatinopopinterp  0.189338868 0.21100140 3.881837e-01
7            medincinterp -0.001439268 0.00383561 7.097029e-01
8       pctrentersinterp -0.629882625 0.23710123 8.897578e-03
9   pctcollegegradinterp  0.486846914 0.48119419 3.187958e-01
10               biracial  0.215510583 0.02819784 1.520803e-08
11            nonpartisan -0.064834230 0.06181155 3.178115e-01
12                primary -0.067327075 0.02246490 3.475962e-03
13                 logpop  0.033340422 0.03063427 2.828310e-01
14   whiteideology_fill2 -0.027578781 0.02151460 2.075705e-01
15             year.f1990 -0.009450522 0.13352336 9.452010e-01
16             year.f1991 -0.004676689 0.05683288 9.347988e-01
17             year.f1992 -0.080365497 0.11793485 5.040218e-01
18             year.f1993  0.001730653 0.05964367 9.768955e-01
19             year.f1994 -0.051833262 0.10874620 6.409745e-01
20             year.f1995 -0.031970530 0.07422024 6.725307e-01
21             year.f1996  0.005376359 0.13244501 9.679063e-01
22             year.f1997 -0.035283231 0.07631290 6.472195e-01
23             year.f1998 -0.166828180 0.15569417 3.012218e-01
```

```
24          year.f1999 -0.049963327 0.08868351 5.830423e-01
25          year.f2000  0.163501084 0.14243864 2.633043e-01
26          year.f2001 -0.053189517 0.08390707 5.339416e-01
27          year.f2002 -0.150864838 0.11003594 1.800189e-01
28          year.f2003 -0.130987638 0.08515400 1.358167e-01
29          year.f2004 -0.103246293 0.11041594 3.676207e-01
30          year.f2005 -0.153377918 0.09521167 1.225700e-01
31          year.f2006 -0.198930433 0.17307381 2.697358e-01
32          year.f2007 -0.161639818 0.09795083 1.166759e-01
33          year.f2008 -0.159312984 0.27620087 5.801481e-01
34          year.f2009 -0.182999459 0.16244234 2.935900e-01
35               south  0.134289154 0.05100857 1.199686e-02
36             midwest  0.125276354 0.05718915 3.438830e-02
37                west  0.028609786 0.05452091 6.020324e-01
```

Appendix

Table 1

Table 2

Table 3

Table 3

Main Analysis 4

Main Analysis 5

Table 5

Appendix

TABLE A2 Cities Included in Racial Polarization Data

Replication

	Segregation: Mean *H* Index		**Largest Racial Divide, Number of Elections**		
City Name	Multigroup	Two-Group	Black/White	Latino/White	Black/Latino
Austin, TX	0.204	0.208	1	0	0
Baltimore, MD	0.510	0.516	3	1	0
Charlotte, NC	0.269	0.287	2	0	0
Chicago, IL	0.572	0.460	7	0	1
Cleveland, OH	0.558	0.531	2	0	0
Columbus, OH	0.316	0.284	3	0	1
Dallas, TX	0.359	0.339	4	0	1

Denver, CO	0.289	0.254	1	2	0
Detroit, MI	0.398	0.255	1	0	1
Houston, TX	0.339	0.308	7	0	2
Indianapolis, IN	0.292	0.293	0	0	1
Jacksonville, FL	0.233	0.222	2	0	0
Los Angeles, CA	0.351	0.366	3	0	5
Memphis, TN	0.470	0.474	2	0	0
Milwaukee, WI	0.423	0.360	3	0	0
New York, NY	0.468	0.474	5	3	1
Oklahoma, OK	0.231	0.165	1	0	0
Philadelphia, PA	0.492	0.487	5	0	0
Phoenix, AZ	0.255	0.270	0	1	0
San Antonio, TX	0.237	0.225	0	4	0
San Diego, CA	0.255	0.266	3	0	1
San Francisco, CA	0.223	0.161	3	0	1
San Jose, CA	0.186	0.198	0	2	1
Tucson, AZ	0.185	0.192	1	0	0
Washington, DC	0.464	0.491	3	0	0

TABLE A3 Summary Statistics: Census of Government Finance and Population

Variable	**Obs**	**Mean**	**SD**	**Min**	**Max**
Direct General Expenditure per Capita	13742	1.186	1.220	0.019	70.457
Highways per Capita	13603	0.081	0.053	0.000	1.106
Parks per Capita	12905	0.061	0.061	0.000	1.111
Police per Capita	13626	0.181	0.094	0.000	1.546
Sewers per Capita	11223	0.092	0.077	0.000	1.591
Welfare, Health, and Housing per Capita	10871	0.057	0.131	0.000	4.984
Own Source Revenue per Capita	13741	0.942	1.118	0.021	76.123
Two-Group H Index	13742	0.076	0.099	0.000	0.767
Diversity	13742	0.309	0.188	0.007	0.772
% Black	13742	0.097	0.151	0.000	0.980
% Asian	13742	0.032	0.054	0.000	0.674
% Latino	13742	0.104	0.161	0.000	0.987
5Y Change, % Black	11194	0.007	0.019	−0.101	0.229
5Y Change, % Latino	11194	0.016	0.020	−0.171	0.207
5Y Change, % Asian	11194	0.005	0.011	−0.056	0.128
Median Income	13742	54,520.132	22,081.359	15,642.802	240,938.047
% Local Gov. Employees	13742	3.359	0.951	0.677	8.365
% Renters	13742	0.360	0.140	0.014	0.871
% Over 65	13742	0.125	0.050	0.012	0.771
% College Degree	13742	0.160	0.099	0.003	0.587
Population (logged)	13742	10.132	1.016	6.071	15.921
City Ideology	2130	4.023	0.780	1.000	7.000
Population	13742	53,723.022	208,143.791	433.000	8,214,426.000

Bibliography

Pencharz, Paul B., and Ronald O. Ball. 2003. “Different Approaches to Define Individual Amino Acid Requirements.” *Annual Review of Nutrition* 23. Annual Reviews: 101–16.

Table 1: **Racial Polarization in Segregated Cities**

	Dependent variable:		
	biggestsplit		
	(1)	(2)	(3)
Multigroup H Index	0.932^{**} (0.394)		
White/Nonwhite H Index		0.756^{**} (0.297)	0.835^{***} (0.296)
Diversity	0.385 (0.362)	0.518 (0.323)	0.584^{*} (0.323)
Percent Asian	−0.115 (0.527)	0.120 (0.558)	−0.004 (0.522)
Percent Black	−0.432 (0.269)	−0.237 (0.216)	−0.133 (0.212)
Percent Latino	−0.191 (0.257)	−0.059 (0.254)	0.095 (0.278)
Medain HH Income (1000s)	−0.004 (0.007)	−0.007 (0.007)	−0.002 (0.006)
Percent Renters	−0.580 (0.422)	-0.806^{*} (0.431)	−0.419 (0.454)
Percent College Degree	0.328 (0.711)	0.723 (0.729)	0.123 (0.869)
Biracial Contest	0.210^{***} (0.037)	0.208^{***} (0.037)	0.192^{***} (0.036)
Nonpartisan Election	−0.090 (0.066)	−0.089 (0.066)	−0.034 (0.065)
Primary Election	-0.092^{***} (0.032)	-0.090^{***} (0.032)	-0.071^{**} (0.030)
Population (logged)	0.035 (0.055)	0.048 (0.055)	−0.011 (0.061)
White Ideology			−0.051 (0.032)
Constant	−0.242 (0.569)	−0.393 (0.563)	0.236 (0.605)
Wald Chi Squarred	a	b	c
Observations	91	91	86
Akaike Inf. Crit.	−55.548	−56.381	−64.922
Bayesian Inf. Crit.	32.332	31.499	20.981
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 2: **Effect of Segregation on Overall per Capita City Expenditures**

	Dependent variable:		
	dgepercap_cpi		
	(1)	(2)	(3)
H_citytract_NHW_i	-1.153^{***}	-1.011^{***}	-1.733^{***}
	(0.221)	(0.254)	(0.437)
diversityinterp	0.106		-0.063
	(0.134)		(0.246)
pctblkpopinterp	0.681^{***}	0.741^{***}	0.164
	(0.167)	(0.161)	(0.523)
pctasianpopinterp	-0.385	-0.852^{**}	0.197
	(0.302)	(0.348)	(0.706)
pctlatinopopinterp	1.543^{***}	1.577^{***}	1.622^{***}
	(0.186)	(0.205)	(0.390)
chng5pctblk		-1.778^{***}	
		(0.644)	
chng5pctlatino		-2.055^{**}	
		(0.823)	
chng5pctasian		-0.800	
		(1.093)	
medinc_cpi	0.002^{*}	0.001	0.004
	(0.001)	(0.002)	(0.003)
pctlocalgovworker_100	0.014	0.006	-0.030
	(0.016)	(0.018)	(0.046)
pctrentersinterp	0.527	0.547	0.336
	(0.333)	(0.385)	(0.656)
pctover65	0.093	0.487	-0.865
	(0.643)	(0.451)	(0.816)
pctcollegegradinterp	5.395^{***}	6.260^{***}	6.527^{***}
	(0.403)	(0.419)	(1.029)
logpop	-0.243^{***}	-0.290^{***}	-0.447^{***}
	(0.044)	(0.068)	(0.088)
ideology_fill			-0.012
			(0.034)
Observations	13,742	11,194	2,130
R^2	0.863	0.897	0.882
Adjusted R^2	0.830	0.865	0.855
Residual Std. Error	0.503 (df = 11094)	0.465 (df = 8544)	0.405 (df = 1741)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 3: **Effect of Segregation on Public Goods A**

	Dependent variable:		
	highwayspercapNC_cpi	policepercapNC_cpi	parkspercapNC_cpi
	(1)	(2)	(3)
H_citytract_NHW_i	-0.039^{**}	-0.215^{***}	-0.046^{***}
	(0.016)	(0.023)	(0.018)
diversityinterp	0.005	0.059^{***}	0.001
	(0.010)	(0.013)	(0.013)
pctblkpopinterp	0.052^{***}	0.142^{***}	0.031^{*}
	(0.014)	(0.018)	(0.018)
pctasianpopinterp	-0.036	-0.055	-0.067^{***}
	(0.026)	(0.035)	(0.023)
pctlatinopopinterp	0.025^{*}	0.335^{***}	0.049^{***}
	(0.014)	(0.019)	(0.014)
medinc_cpi	0.0003^{**}	0.00004	-0.00002
	(0.0001)	(0.0001)	(0.0001)
pctlocalgovworker_100	-0.0003	-0.001	0.001
	(0.001)	(0.002)	(0.001)
pctrentersinterp	0.011	0.075^{***}	0.018
	(0.023)	(0.028)	(0.021)
pctover65	0.140^{***}	0.147^{***}	0.127^{***}
	(0.032)	(0.045)	(0.040)
pctcollegegradinterp	0.218^{***}	0.793^{***}	0.444^{***}
	(0.026)	(0.038)	(0.038)
logpop	-0.015^{***}	-0.054^{***}	-0.005^{*}
	(0.004)	(0.004)	(0.003)
Observations	13,603	13,626	12,905
R^2	0.571	0.837	0.750
Adjusted R^2	0.467	0.798	0.688
Residual Std. Error	0.039 (df = 10958)	0.042 (df = 10991)	0.034 (df = 10321)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 4: **Effect of Segregation on Public Goods B**

	Dependent variable:		
	sewerspercapNC_cpi	welfhoushealthNC_cpi	genrevownpercap_cpi
	(1)	(2)	(3)
H_citytract_NHW_i	-0.148^{***}	-0.138^{***}	-0.768^{***}
	(0.022)	(0.049)	(0.155)
diversityinterp	0.039^{***}	-0.033	0.091
	(0.015)	(0.025)	(0.085)
pctblkpopinterp	0.012	0.016	0.272^{**}
	(0.017)	(0.056)	(0.120)
pctasianpopinterp	-0.124^{***}	0.130	-0.147
	(0.044)	(0.090)	(0.233)
pctlatinopopinterp	0.091^{***}	0.140^{***}	1.202^{***}
	(0.019)	(0.028)	(0.120)
medinc_cpi	0.001^{***}	-0.0003	0.004^{***}
	(0.0002)	(0.0003)	(0.001)
pctlocalgovworker_100	-0.004^{*}	-0.007^{**}	0.002
	(0.002)	(0.003)	(0.013)
pctrentersinterp	0.174^{***}	0.079^{*}	0.569^{**}
	(0.034)	(0.046)	(0.263)
pctover65	0.104^{*}	-0.058	0.443
	(0.053)	(0.070)	(0.471)
pctcollegegradinterp	0.286^{***}	0.421^{***}	4.331^{***}
	(0.043)	(0.080)	(0.349)
logpop	-0.023^{***}	-0.012^{*}	-0.126^{***}
	(0.003)	(0.007)	(0.032)
Observations	11,223	10,871	13,741
R^2	0.675	0.828	0.886
Adjusted R^2	0.586	0.777	0.859
Residual Std. Error	0.049 (df = 8805)	0.062 (df = 8380)	0.420 (df = 11093)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 5: **Effect of Segregation on Public Goods**

	Dependent variable:					
	highwayspercapNC_cpi	policepercapNC_cpi	parkspercapNC_cpi	sewerspercapNC_cpi	welfhoushealthNC_cpi	genrevownp
	(1)	(2)	(3)	(4)	(5)	(6
H_citytract_NHW_i	−0.039**	−0.215***	−0.046***	−0.148***	−0.138***	−0.7
	(0.016)	(0.023)	(0.018)	(0.022)	(0.049)	(0.1
diversityinterp	0.005	0.059***	0.001	0.039***	−0.033	0.0
	(0.010)	(0.013)	(0.013)	(0.015)	(0.025)	(0.0
pctblkpopinterp	0.052***	0.142***	0.031*	0.012	0.016	0.27
	(0.014)	(0.018)	(0.018)	(0.017)	(0.056)	(0.1
pctasianpopinterp	−0.036	−0.055	−0.067***	−0.124***	0.130	−0.
	(0.026)	(0.035)	(0.023)	(0.044)	(0.090)	(0.2
pctlatinopopinterp	0.025*	0.335***	0.049***	0.091***	0.140***	1.20
	(0.014)	(0.019)	(0.014)	(0.019)	(0.028)	(0.1
medinc_cpi	0.0003**	0.00004	−0.00002	0.001***	−0.0003	0.00
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0003)	(0.0
pctlocalgovworker_100	−0.0003	−0.001	0.001	−0.004*	−0.007**	0.0
	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.0
pctrentersinterp	0.011	0.075***	0.018	0.174***	0.079*	0.56
	(0.023)	(0.028)	(0.021)	(0.034)	(0.046)	(0.2
pctover65	0.140***	0.147***	0.127***	0.104*	−0.058	0.4
	(0.032)	(0.045)	(0.040)	(0.053)	(0.070)	(0.4
pctcollegegradinterp	0.218***	0.793***	0.444***	0.286***	0.421***	4.33
	(0.026)	(0.038)	(0.038)	(0.043)	(0.080)	(0.3
logpop	−0.015***	−0.054***	−0.005*	−0.023***	−0.012*	−0.1
	(0.004)	(0.004)	(0.003)	(0.003)	(0.007)	(0.0
Observations	13,603	13,626	12,905	11,223	10,871	13,
R^2	0.571	0.837	0.750	0.675	0.828	0.8
Adjusted R^2	0.467	0.798	0.688	0.586	0.777	0.8
Residual Std. Error	0.039 (df = 10958)	0.042 (df = 10991)	0.034 (df = 10321)	0.049 (df = 8805)	0.062 (df = 8380)	0.420 (df

Note: *p<0.1; **p<0.05;

Table 6: **Effect of Segregation on City Expenditures, IV Approach A**

	Dependent variable:			
	dgepercap_cpi	highwayspercapNC_cpi	policepercapNC_cpi	parkspercapNC_cp
	(1)	(2)	(3)	(4)
H_citytract_NHW_i	−2.676***	−0.363***	−0.350***	−0.034*
	(0.935)	(0.056)	(0.109)	(0.019)
dgepercap_cpilag	1.472***			
	(0.007)			
highwayspercapNC_cpilag		0.477***		
		(0.003)		
policepercapNC_cpilag			0.955***	
			(0.004)	
parkspercapNC_cpilag				0.869***
				(0.006)
diversityinterp	0.264	−0.032	−0.020	0.004
	(0.355)	(0.022)	(0.042)	(0.007)
pctblkpopinterp	0.376	0.085***	0.096**	0.003
	(0.325)	(0.020)	(0.038)	(0.007)
pctasianpopinterp	0.143	−0.111**	−0.064	−0.022
	(0.940)	(0.056)	(0.110)	(0.019)
pctlatinopopinterp	0.087	0.088***	0.088***	0.007
	(0.284)	(0.017)	(0.033)	(0.006)
medincinterp	−0.004	0.001***	0.001***	0.0002***
	(0.003)	(0.0002)	(0.0004)	(0.0001)
pctlocalgovworker_100	−0.104***	0.021***	0.026***	0.003***
	(0.032)	(0.002)	(0.004)	(0.001)
pctrentersinterp	−0.553	0.165***	0.187***	0.035***
	(0.350)	(0.021)	(0.041)	(0.007)
pctover65	0.301	0.267***	0.238***	0.072***
	(0.730)	(0.044)	(0.086)	(0.015)
pctcollegegradinterp	0.248	−0.044	−0.101	0.028**
	(0.567)	(0.034)	(0.067)	(0.012)
Constant	0.328	−0.125***	−0.183***	−0.029***
	(0.278)	(0.017)	(0.033)	(0.006)
Observations	21,145	20,704	20,627	19,056
R^2	0.685	0.615	0.789	0.540
Adjusted R^2	0.685	0.615	0.789	0.539
Residual Std. Error	4.877 (df = 21125)	0.290 (df = 20684)	0.566 (df = 20607)	0.093 (df = 19036)
Note:				*p<0.1; **p<0.05; ***p<0.0

Table 7: **Effect of Segregation on City Expenditures, IV Approach B**

	Dependent variable:		
	sewerspercapNC_cpi	genrevownpercap_cpi	welfhoushealthNC_cpi
	(1)	(2)	(3)
H_citytract_NHW_i	-0.363^{***}	-1.873^{**}	-0.115^{**}
	(0.060)	(0.789)	(0.054)
sewerspercapNC_cpilag	0.064^{***}		
	(0.008)		
genrevownpercap_cpilag		1.235^{***}	
		(0.006)	
welfhoushealthNC_cpilag			0.893^{***}
			(0.005)
diversityinterp	0.080^{***}	0.047	-0.047^{**}
	(0.024)	(0.300)	(0.022)
pctblkpopinterp	0.058^{**}	0.360	0.076^{***}
	(0.025)	(0.274)	(0.023)
pctasianpopinterp	-0.223^{***}	-0.029	0.009
	(0.068)	(0.793)	(0.053)
pctlatinopopinterp	-0.050^{***}	0.206	0.078^{***}
	(0.019)	(0.240)	(0.017)
medincinterp	0.0002	0.0003	0.001^{**}
	(0.0003)	(0.003)	(0.0002)
pctlocalgovworker_100	0.001	-0.003	0.016^{***}
	(0.002)	(0.027)	(0.002)
pctrentersinterp	0.073^{***}	0.263	0.098^{***}
	(0.024)	(0.295)	(0.023)
pctover65	0.287^{***}	0.782	0.127^{**}
	(0.051)	(0.616)	(0.050)
pctcollegegradinterp	0.029	-0.035	-0.038
	(0.040)	(0.478)	(0.038)
Constant	0.004	-0.174	-0.093^{***}
	(0.019)	(0.234)	(0.018)
Observations	16,616	21,148	14,711
R^2	0.006	0.681	0.699
Adjusted R^2	0.005	0.681	0.698
Residual Std. Error	0.284 (df = 16596)	4.115 (df = 21128)	0.252 (df = 14691)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 8: **TABLE A1 Summary Statistics: Racial Polarization Data**

Statistic	N	Mean	St. Dev.	Min	Max
Largest Racial Divide	91	0.481	0.213	0.016	0.934
H Index: Multigroup	91	0.376	0.119	0.183	0.635
H Index: Two-Group	91	0.353	0.114	0.156	0.614
Diversity	91	0.623	0.088	0.323	0.736
% Asian	91	0.067	0.074	0.008	0.318
% Black	91	0.275	0.181	0.030	0.815
% Latino	91	0.229	0.155	0.009	0.605
Median HH Income	91	36.725	10.114	17.267	75.982
% Renters	91	0.535	0.092	0.368	0.718
% College Degree	91	0.167	0.056	0.049	0.359
Biracial Contest	91	0.725	0.449	0	1
Nonpartisan Election	91	0.714	0.454	0	1
Primary Election	91	0.352	0.480	0	1
Population (logged)	91	14.166	0.826	13.065	15.921
White Ideology	86	3.835	0.648	2.667	5.250

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