Milestone 7

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Abstract

Trounstine (2016) suggests that high levels of residential segregation are associated with increased political polarization and decreased public spending. In this analysis, I was able to successfully replicate Trounstine (2016)'s main results. Adding onto her original analysis, I impute a large amount of missing data from the original dataset and re-run the analysis. Finally, I add in income segregation as a predictor in her regressions to assess whether this could be a confounding variable.

Introduction

There is a large degree of variation in public goods spending across local governments. As a result, many scholars have worked to determine what factors may lead to the underprovision of public goods spending. Some scholars in the past have associated racial diversity or changes in levels of diversity with the under-provision of public goods (**???**; **???**). However, Trounstine (2016) argues that it is racial segregation, not diversity in and of itself, that results in the under-provision of public goods. Trounstine's analysis consists of two main parts. First, she uses election and demographic data from 25 of America's largest cities between 1990 and 2010 to run a multilevel mixed-effects linear regression with fixed effects for region and year and with random effects for cities in order to show that polarization increases with 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 second main part of Trounstine's analysis looks at the ability of the Theil's H segregation index to explain a variety of types of public expenditures by city using a sample of 2,637 cities with 13,742 city-year observations. Using linear regressions with fixed effects for cities and robust standard errors clustered by city, Trounstine finds a significant, negative correlation between segregation and public goods spending that is robust to the inclusion of a variety of relevant controls and an alternative specification in which the number of waterways is used as an instrument for segregation.

In this analysis, I first work to replicate the main results of Trounstine (2016) using R statistical software (**???**). The original data and Stata code made publically available by the author were downloaded via the Harvard Dataverse (**???**). I also make all of my code and analysis available on Github.[1] I was successfully able to replicate the main results of Trounstine (2016) in R with the exception of some of the marginal analyses, which I was nevertheless able to replicate in Stata.

```
# calculate number of original observations

obs_fin_seg <- nrow(fin_imp)
obs_rp <- nrow(rp_impute)
```

One concern with the original analysis in Trounstine (2016) is the large amount of missing data, which substantially constrains the sample size used in the regression analysis. For example, the regression analysis in the main specification using the the original racial polarization exludes %0.5517241 of the observations in the

[1] Link to my Github repository for this project.

original dataset, and the regression analysis in the main specification using the original financial segregation data excludes %0.9545017 of observations from the original dataset. As an extension of Trounstine (2016), I impute missing values in the original data using the mice package in R, which generates multivariate imputations using chained equations (**???**). Then, I use the imputed datasets to re-estimate the original models, pooling the results to final pooled regression coefficients and parameters.

Comparing the results of the original regressions and those done with the imputed data yields similar big picture results in terms of the direction of the signs on the coefficients on the segregation indices. Like in Trounstine (2016), I find that segregation is positively associated with political polarization and negatively associated with spending on public goods. However, the magnitude of the effects in most specifications has dminished and most results become statistically insignificant. While these findings do not necessarily challenge the results of Trounstine (2016), they do call into question the relative importance of segregation in determining public goods spending and political polarization and suggest that the results of Trounstine (2016) may not be quite as robust as once thought.

Literature Review

Despite some progress made towards racial equity in the U.S. on other fronts, residential racial segregation in U.S. neighborhoods continues to be prevasive and deeply entrenched in society (**???**; **???**; **???**). Research suggests that this kind of segregation has political consequences, as political cleavages in segregated cities tend to have racial as well as spatial dimensions (**???**). Neighborhoods are often important actors within local politics because local governments provide many functions that are allocational in nature and concern geographical space (Trounstine 2016). Thus, when neighborhoods are divided on racial lines as well as spacial lines, it is natural to expect higher degrees of racial polarization as a result.

Studying residential segregation is difficult because its effects tend to differ by geographic level. On the neighborhood level, the kind of geographic racial isolation brought on by residential segregation has been associated with racial intolerance, resentment, and competition between racial groups (**???**). Living within segregated neighborhoods has also been associated with holding negative stereotypes and perceptions about out groups (**???**). As a result, homogeneous neighborhoods have been associated with increased racial tension and political polarization in comparison to integrated, diverse neighborhoods. However, at the city or metropolitan level, the opposite seems to be true: when considering larger geographic areas, diversity and integration are correlated with racial tension, competition, prejudice, lower levels of cooperation, and lower spending on public goods (**???**; **???**; **???**). While these differences in the expected effect of segregation on the geographic level may seem confusing at first, they make sense as they suggest that the most severely segregated area is one that is diverse overall, but has many homogeneous neighborhoods. Thus, while people of different races co-exist within a highly segregated city, they live separately within their own neighborhoods, which creates an environment ripe for racial antagonism (Trounstine 2016). It is thus not simply the level of diversity or integration that matters for racial harmony and cooperation, but their patterns within a larger geographic framework (Trounstine 2016; **???**; **???**).

Political polarization along racial lines may lead to decreased public spending and goods provision because groups may have different preferences, which can make compromise hard, and because groups may preceive a disutility in out-groups receiving public goods expenditure (**???**). (**???**) found evidence that racial segregation predicts large political divisions at the metropolitan level and that these divisions can create a lack of willingness to compromise and collaborate on local policy problems. Trounstine (2016) finds similar results at the city level: that residential racial segregation is associated with both increased political division and decreased public spending. Thus, these authors suggest that it is the combination of homogenous neighborhoods within a much larger, diverse geographic area that leads to increased political polarization and reduced public goods spending in local governments.

More recently, some scholars have called this hypothesis and its importance into question. For example, (**???**) finds evidence that larger inequalities within the political system favoring socially powerful groups, not local diversity patterns leading to decreased cooperation, may be a better explanation of failures in public goods provision in diverse areas. Other suggests that additional factors, such as income segregation, may be important confounding factors in public goods provision. (**???**), for example, suggests that the more closely related income inequality is to racial inequality, the less investment is made in public goods, and that this interaciton was a better predictor of public goods spending patterns than measures of diversity. inequality and diversity jointly. A variety of evidence suggests that it is meaningful to consider the effects of income inequaltiy and diversity and segregation jointly (**???**; **???**). Given the active debate in the literature over the relaitonships between diversity, segregation, public spending, and other factors, it is increasingly important to re-examine previously reported findings as a means of robustness checks.

Replication

For the most part, results from Trounstine (2016) were successfully replicated. All regressions and tables were fully replicated in R. However, I was unable to successfully replicate Trounstine (2016)'s marginal effects analyses and margins plots using R. There does not yet appear to be a built-in R function to calculate marginal or predicted effects or to generate margins plots from the complicated multi-level models employed in the original paper, and creating such a function was outside of the scope of this analysis. Nevertheless, these results were successfully replicated in Stata.

There was one interesting outcome from my attempt to replicate the original Stata code in R. Due to the differences in R and Stata in dealing with missing values, my first replication of analyses using the financial segregation dataset were slightly different than the results in Stata from the original paper. In order to exclude cities from her analysis with only one census tract, Trounstine conditions her regressions in Stata such that the value for the number of census tracts is greater than one. In Stata, this does not remove missing values, whereas in R, it does. Since this variable is used only as a conditional filter and not as a regression variable (and thus, the observations with missing values for number of census tracts are not dropped), Trounstine's analysis includes 14 cities and 58 observations with missing values for census tracts in addition to cities with two or more census tracts. This is a potential oversight on the part of the author, and I would suggest also dropping observations with missing census tract data, or else imputing them. Nevertheless, dropping these values did not have much of an effect on the subsequent results.

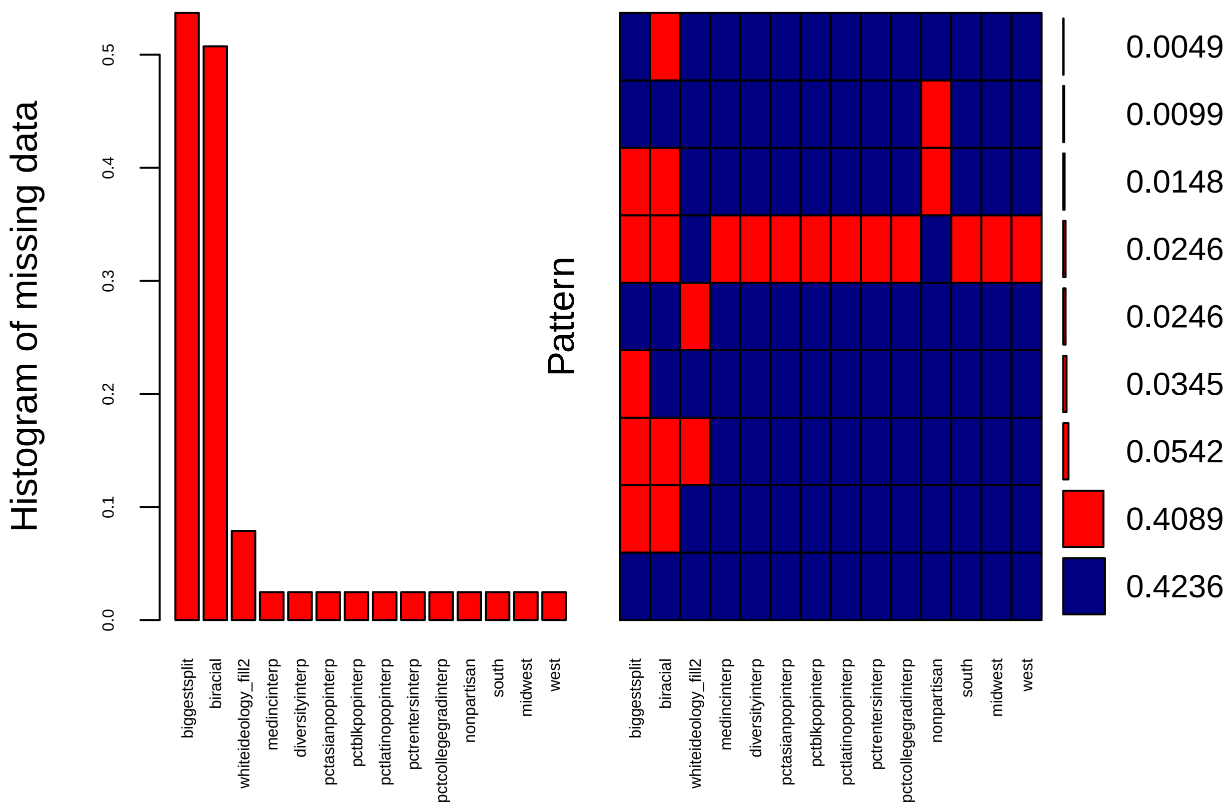
Extension

One concern with the original analysis in Trounstine (2016) is the large amount of missing data values in her original datasets. Because both R and Stata drop any observations with missing values for any of the variables used in a regression, this can exlcude a large portion of the data from the analysis and potentially bias the results if the data is not missing completely at random. A large amount of data is missing in both of the main datasets used in the analyses of Trounstine (2016). The main model specification using the racial polarization dataset exludes 112 of the original 203 observations, or %55.17 of the data. Additionally, the main model specification using the financial segregation data set excludes 2.88291×10^5 of the original 302033 observations, or %95.45 of observations from the original dataset.

In an attempt to better deal with the problem of missing data in Trounstine (2016), I impute missing values in the original data using the mice package in R, which generates multivariate imputations using chained equations (**???**). While there are a variety of different imputation methods that could have been employed, multiple imputation (such as the multiple multivariate imputations generated by mice) is desireable because instead of inputting a single value such as the mean for missing values, it instead uses the distribution of the available data to estimate multiple potential values for the missing data. As a result, multiple imputation helps to account for the uncertainty inherent in the imputation process and allows for the calculation of standard errors around estimaotrs. As a result, multiple imputation allows the researcher to more accurately assess the of uncertainty in the analysis in general.

Before performing the multiple imputations on the datasets, I first examined the missing data for patterns.

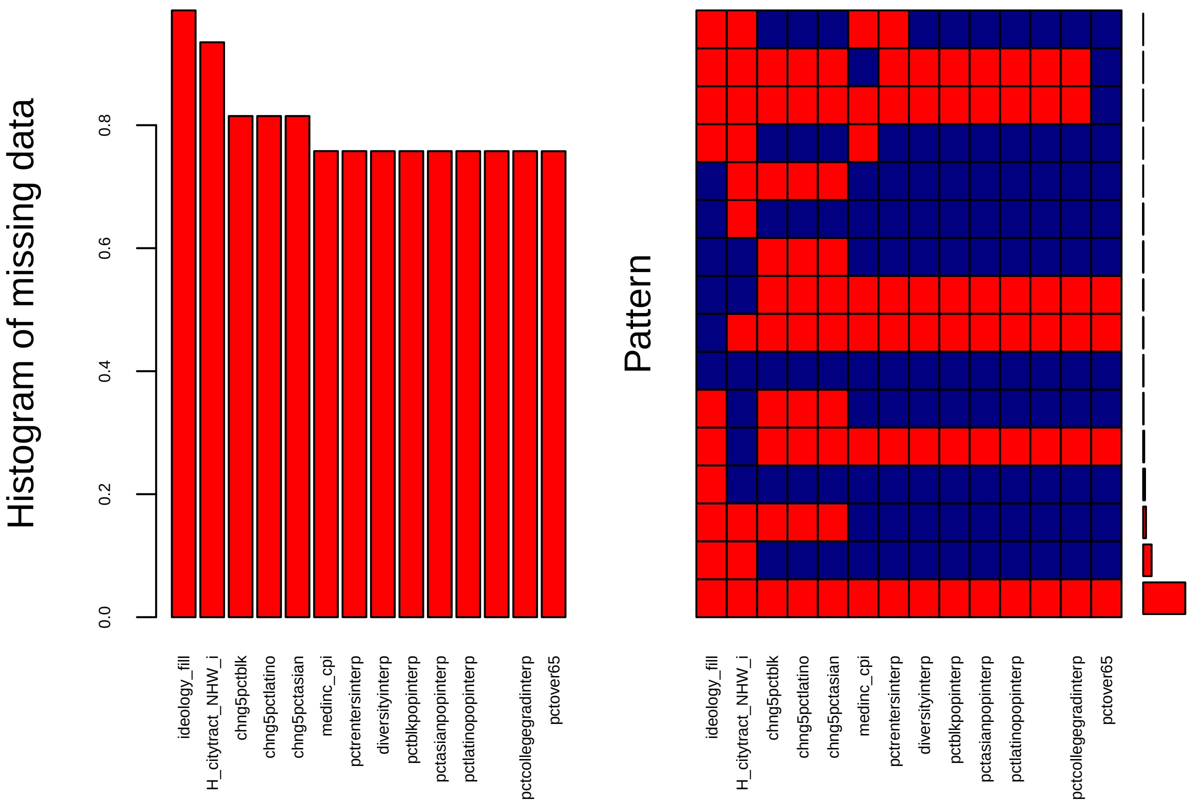
To better understand any potential patterns in missing data, I plotted the pattern of missingness for only and created a histogram showing the frequency of missing values for those variables with missing values in figure X1 for the racial polarization data and figure X2 for the financial segregation data. Looking at figure X1, the histogram shows that the variables for the largest vote split along racial lines and the variable indicating whether or not the election had candidates of more than one race had by far the largest percentages of missing data, missing %53.69 and %50.74, respectively. It is important to note that the variable for the largest vote split along racial lines is the dependent variable in the regresison analysis, and thus, we are missing a large percentage of this key variable. From the plot on the right, we can see that approximately 42% of observations are complete (have no missing values). 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.




```
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
```

In figure X2, we can similarly observe the trends for the financial segregation dataset. In this dataset, there is a very high proportion of missing variables for a number of variables. For example, there are a 282334 missing values for the segregation index, which is the main independent variable, or %93.48 of the data. In this dataset, there are also many more observations for which values are missing for multiple variables in comparison to the racial polarization dataset. In total, a mere %0.58 of observations are complete for all variables included in the main specification for the financial segregaion dataset.

```
Warning in plot.aggr(res, ...): not enough horizontal space to display
frequencies
```



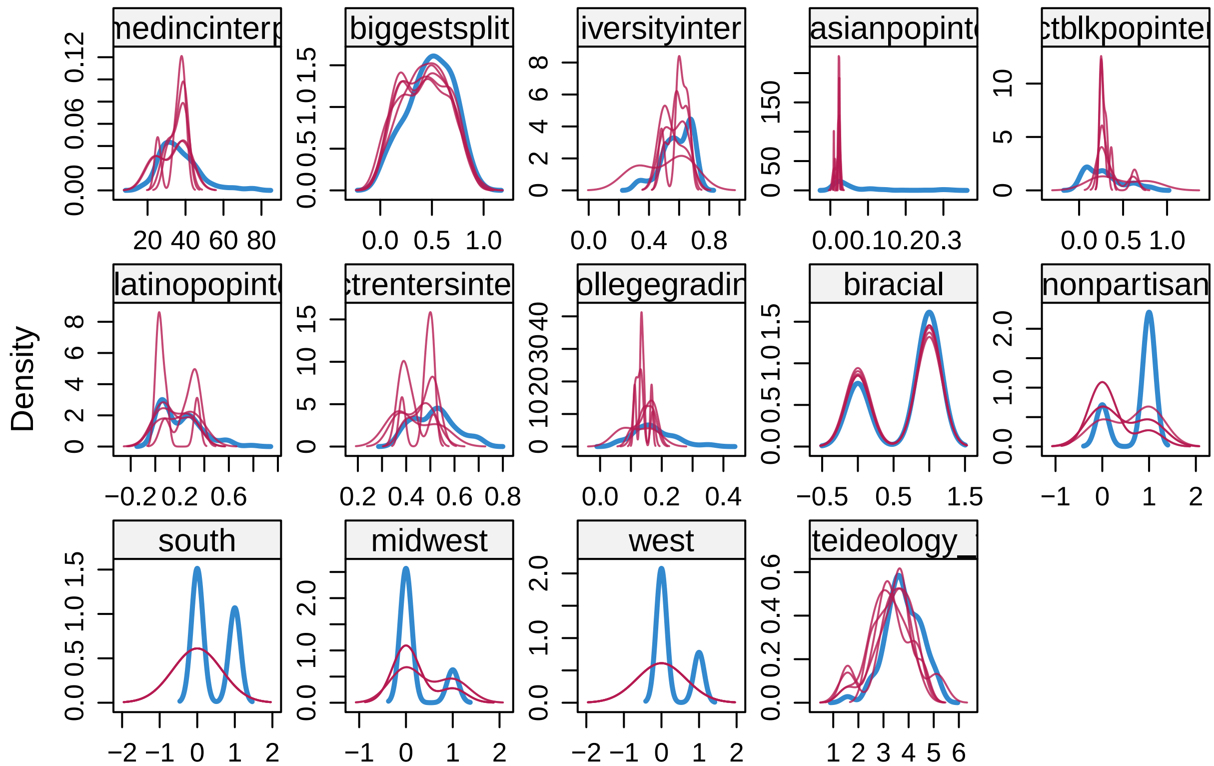

```
 Variables sorted by number of missings:
              Variable     Count
         ideology_fill 0.9866041
     H_citytract_NHW_i 0.9347787
           chng5pctblk 0.8148547
        chng5pctlatino 0.8148547
         chng5pctasian 0.8148547
            medinc_cpi 0.7578741
      pctrentersinterp 0.7577980
       diversityinterp 0.7577914
       pctblkpopinterp 0.7577914
     pctasianpopinterp 0.7577914
    pctlatinopopinterp 0.7577914
 pctlocalgovworker_100 0.7577914
  pctcollegegradinterp 0.7577914
             pctover65 0.7576722
```

```
[1] 1751.791
```

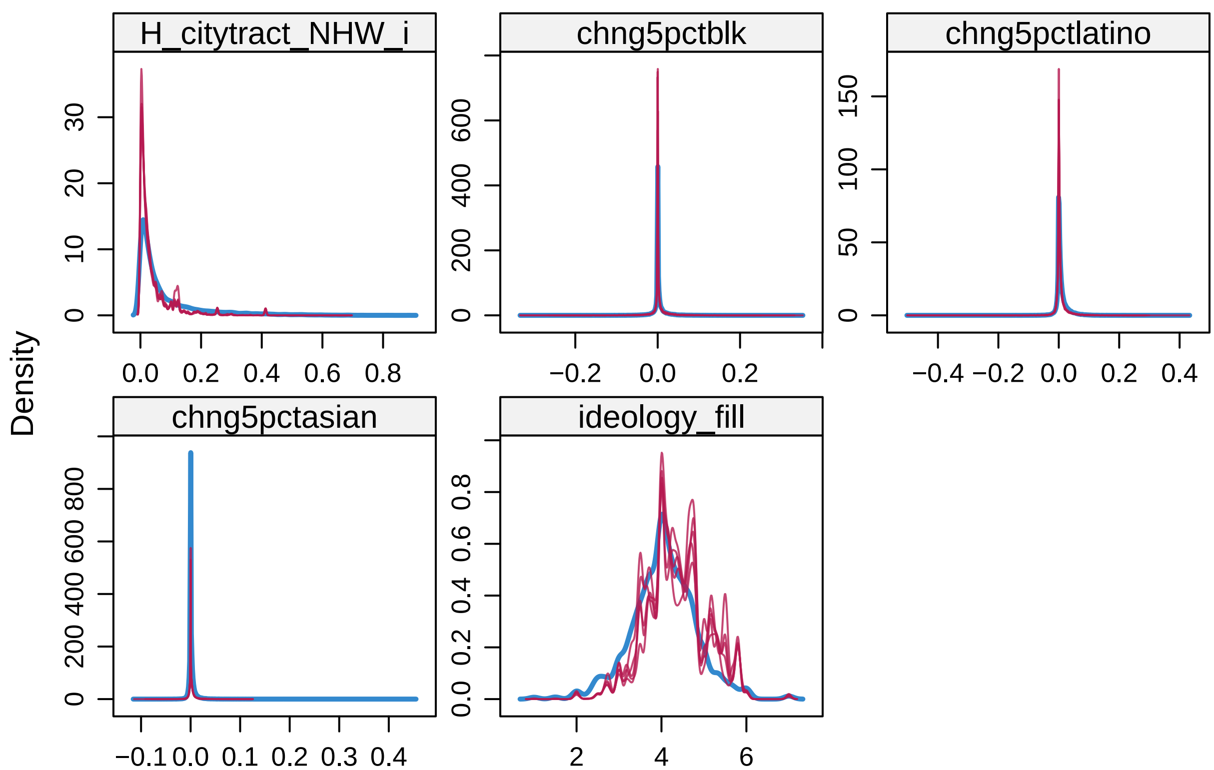
Because neither dataset seems to exhibit any clear patterns in the missing, data, it makes sense to proceed with the imputation. For the racial polarization dataset, I performed multiple imputations with 20 iterations using mice, while for the financial segregation dataset, I performed only 5 iterations due to the large size of the dataset and computing limitaitons. A non-stochastic imputation method, Classification and Regression Trees (CART), was used instead of the default for the imputation for both datasets because of an error with matrix inversion caused by the data that prevented the use of the default method, predictive mean matching. For the racial polarization dataset, I included all of the variables used in the analysis associated with the dataset and was able to impute all missing values. For the financial segregation dataset, however, I only imputed values for the main independent variable, the segregation index, and a few other variables, although all variables used in the analysis were included in the data subset input into the mice function. More of the data could not be imputed from the financial segregation dataset due to computing and time constraints for this project given the dataset's large size and proportion of missing values.

make sure to talk about the fact that still a large number of values missing for the imputed variables here

Before examining the results of Trounstine's model using the multiply imputed data, I first ran some diagnostic tests on the imputation results to make sure that everything ran as expected. First, I checked the convergence of the algorithm used within mice() by plotting the trace lines as a function of the number of iterations for each of the variables. Then, I visually inspected the distributions of the imputed data in comparison to the original data with density and strip plots. All of these checks suggested that the imputed values were within a plausible range of the data and that their distribution fit the underlying distribution of the data relatively well. The only cases in which there was some cause for concern were for some of the variables with very few missing values in the racial polarization dataset (such as the indicators for region). However, this is more or less to be expected given the small number of imputations performed in these cases. Thus, and especially because there are so few of these values in the actual imputed datasets, this was not a major concern. See figures X and X1 to see the density plots of the imputed values overlayed on the density plots of the original variables. The rest of the plots and results of the diagnostic tests discussed here are presented in the Appendix.




```
Error in density.default(x = c(NA_real_, NA_real_, NA_real_, NA_real_, : need at least 2 points to sele
```



Given the promising results of the diagnostic checks, I next proceeded to re-estimate the original model using the multiply imputed datasets, pooling the results to produce final pooled regression coefficients and parameters. The results for the analyses using the racial polarization dataset are presented in tables 1-3.

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.

```
                    term     estimate   std.error     p.value
1            (Intercept)  0.102790142 0.493934326 0.837614939
2   H_citytract_multi_i  0.453326497 0.348694304 0.205951039
3        diversityinterp  0.123967102 0.312377696 0.693743276
4     pctasianpopinterp -0.074241964 0.444583120 0.868590049
5       pctblkpopinterp  0.207899537 0.193167426 0.287790076
6    pctlatinopopinterp  0.163002438 0.204286528 0.432303470
7           medincinterp  0.001562794 0.004287399 0.717720249
8      pctrentersinterp -0.419230064 0.297441281 0.166170001
9  pctcollegegradinterp  0.307747279 0.611607314 0.622253286
10              biracial  0.188377352 0.038608047 0.000590573
11           nonpartisan -0.064507988 0.056677862 0.265434489
12               primary -0.048685964 0.027900379 0.093728871
13                logpop  0.009863395 0.042472137 0.819901297

% Error: Argument 'header' must be of type 'logical' (TRUE/FALSE)
```

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.

```
                    term    estimate   std.error      p.value
1            (Intercept)  0.06359131 0.485904355 0.8973585131
2      H_citytract_NHW_i  0.58781597 0.258004304 0.0270850500
3        diversityinterp  0.07233701 0.287492968 0.8027800741
4     pctasianpopinterp  0.13801742 0.456035952 0.7643173911
5       pctblkpopinterp  0.21298251 0.168036405 0.2117744468
6    pctlatinopopinterp  0.20511675 0.213275459 0.3485866272
7           medincinterp  0.00050681 0.004346694 0.9079867879
8      pctrentersinterp -0.51495197 0.300841418 0.0947111090
9  pctcollegegradinterp  0.46544162 0.625563151 0.4695679555
10              biracial  0.18726958 0.038984753 0.0007818527
11           nonpartisan -0.04836187 0.056358296 0.3986015846
12               primary -0.04750543 0.027579664 0.0977656454
13                logpop  0.01227514 0.041592434 0.7722869246

% Error: Argument 'header' must be of type 'logical' (TRUE/FALSE)
```

```
                    term    estimate   std.error     p.value
1            (Intercept)  0.03161226 0.494480802 0.949809318
2      H_citytract_NHW_i  0.56382756 0.257506957 0.033361645
3        diversityinterp  0.11339515 0.278801961 0.686073897
4     pctasianpopinterp  0.17314648 0.461168461 0.710306652
```

```
5       pctblkpopinterp  0.23765154 0.171764553 0.174915825
6    pctlatinopopinterp  0.19193817 0.209104301 0.369550944
7          medincinterp  0.00129454 0.004451916 0.773565336
8      pctrentersinterp -0.57173192 0.315168406 0.079913167
9  pctcollegegradinterp  0.30239740 0.625335770 0.635705666
10             biracial  0.18115919 0.040312506 0.001464491
11          nonpartisan -0.04181535 0.054897786 0.451931475
12              primary -0.04646529 0.027383436 0.102509685
13               logpop  0.02233954 0.044099579 0.621581568
```

```
% Error: Argument 'header' must be of type 'logical' (TRUE/FALSE)
```

For the financial segregation dataset, we similarly fit each of our 5 imputed datasets to the original models from Trounstine (2016) using this data and then pool the results for each. The results are presented in tables 4-6.

FS data results

```
# Main Analysis 2: Imputations


## regression 1 Table 2

# fit multiple imputed datasets

fit_imp_felm1 <- with(imp_1_fs, felm(dgepercap_cpi ~ H_citytract_NHW_i + diversityinterp + pctblkpopint

# pool the analyses

pool_imp_felm1 <- pool(fit_imp_felm1)
imp_felm1_sum <- summary(pool_imp_felm1)


## regression 2 Table 2

# fit multiple imputed datasets

fit_imp_felm2 <- with(imp_1_fs, felm(dgepercap_cpi ~ H_citytract_NHW_i + pctblkpopinterp + pctasianpopi

# pool the analyses

pool_imp_felm2 <- pool(fit_imp_felm2)
imp_felm2_sum <- summary(pool_imp_felm2)



## Regression 3 Table 2

fit_imp_felm3 <- with(imp_1_fs, felm(dgepercap_cpi ~ H_citytract_NHW_i + diversityinterp + pctblkpopint

# pool the analyses
```

```r
pool_imp_felm3 <- pool(fit_imp_felm3)
imp_felm3_sum <- summary(pool_imp_felm3)
```

The results of the first regression indicate that Trounstine's results are robust to the inclusion of the imputed data, which led to the inclusion of an additional 59,377 observaitons in the analysis. The coefficients, standard errors, and significance levels are essentially unchanged. The same is largely true for the second and third specifications, but the magnitude of the coefficient on the segregation decreases by a marginal amount.

```
                    term     estimate   std.error      p.value
1      H_citytract_NHW_i -1.128987582 0.217486324 2.247537e-07
2        diversityinterp  0.110597185 0.133880537 4.088274e-01
3        pctblkpopinterp  0.671669182 0.166602751 5.695232e-05
4      pctasianpopinterp -0.393163408 0.301762420 1.927240e-01
5     pctlatinopopinterp  1.541083956 0.185608167 0.000000e+00
6             medinc_cpi  0.002089921 0.001177288 7.597837e-02
7  pctlocalgovworker_100  0.013743747 0.016276571 3.985278e-01
8       pctrentersinterp  0.562609738 0.330586403 8.889872e-02
9              pctover65  0.082921625 0.639036583 8.967658e-01
10  pctcollegegradinterp  5.393995988 0.401137386 0.000000e+00
11                logpop -0.239657940 0.043422921 3.732514e-08

% Error: Argument 'header' must be of type 'logical' (TRUE/FALSE)
```

```
                    term      estimate   std.error      p.value
1      H_citytract_NHW_i -0.9779977874 0.248662965 8.601867e-05
2        pctblkpopinterp  0.7318797293 0.160451106 5.310049e-06
3      pctasianpopinterp -0.8562981609 0.347888919 1.390167e-02
4     pctlatinopopinterp  1.5852109567 0.204045137 1.110223e-14
5            chng5pctblk -1.7632041404 0.639145278 5.842741e-03
6         chng5pctlatino -2.1166687349 0.820811885 9.968712e-03
7          chng5pctasian -0.6475206753 1.091335099 5.530111e-01
8             medinc_cpi  0.0008628414 0.002113666 6.831445e-01
9  pctlocalgovworker_100  0.0048757739 0.018105973 7.877266e-01
10      pctrentersinterp  0.6212719298 0.379424166 1.016627e-01
11             pctover65  0.4709450690 0.446862248 2.920268e-01
12  pctcollegegradinterp  6.2592352486 0.416903707 0.000000e+00
13                logpop -0.2846663823 0.067121497 2.300019e-05

% Error: Argument 'header' must be of type 'logical' (TRUE/FALSE)
```

```
                    term     estimate   std.error      p.value
1      H_citytract_NHW_i -1.581411153 0.405268425 1.111203e-04
2        diversityinterp -0.048958872 0.243406896 8.406862e-01
3        pctblkpopinterp  0.108424725 0.510233272 8.318196e-01
4      pctasianpopinterp  0.138165215 0.699935996 8.436122e-01
5     pctlatinopopinterp  1.591787919 0.385586279 4.409200e-05
6             medinc_cpi  0.003699289 0.002839496 1.933561e-01
7  pctlocalgovworker_100 -0.030893074 0.041722035 4.594400e-01
8       pctrentersinterp  0.574568589 0.634192519 3.654626e-01
9              pctover65 -0.926311969 0.781150804 2.363586e-01
10  pctcollegegradinterp  6.583401879 1.007600099 1.855924e-10
11                logpop -0.422012560 0.085633983 1.196070e-06
12         ideology_fill -0.006270257 0.032811947 8.485420e-01
```

```
% Error: Argument 'header' must be of type 'logical' (TRUE/FALSE)
```

Extension 1

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:

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.

Extension Part 2: Fin Seg Data Set

In the second, and arguably most important dataset in the analysis, the data set on financial segregation, there are a very large number of missing values.

Finding no clear patterns in the missing data, I next performed mutliple imputations (with 5 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.

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:

Regression 1

The results of the first regression indicate that Trounstine's results are robust to the inclusion of the imputed data. The coefficients, standard errors, and significance levels are essentially unchanged. The same is largely true for the second and third specifications, but the magnitude of the coefficient on the segregation decreases by a marginal amount.

```
# how many observations were included in those 3 analyses?

# basic filter for table for all regressions

# xtreg dgepercap_cpi H_citytract_NHW_i diversityinterp pctblkpopinterp
# pctasianpopinterp pctlatinopopinterp medinc_cpi pctlocalgovworker_100
# pctrentersinterp pctover65 pctcollegegradinterp logpop if totaltracts>1 &
# dgepercap_cpi~=0,fe vce(cluster geo_id2)

sum(is.na(complete(imp_2_fs)$H_citytract_NHW_i))
```

```
[1] 222957
```

```
sum(is.na(complete(imp_2_fs,1)$H_citytract_NHW_i))
```

```
[1] 222957
```

```
sum(is.na(complete(imp_2_fs,2)$H_citytract_NHW_i))
```

```
[1] 222957
```

```
sum(is.na(complete(imp_2_fs,3)$H_citytract_NHW_i))
```

```
[1] 222957
```

```
sum(is.na(complete(imp_2_fs,4)$H_citytract_NHW_i))
```

```
[1] 222957
```

```
sum(is.na(complete(imp_2_fs,5)$H_citytract_NHW_i))
```

```
[1] 222957
```

```
fin <- complete(imp_2_fs) %>%
  filter(!(is.na(dgepercap_cpi)), !(is.na(H_citytract_NHW_i)), !(is.na(diversityinterp)),
         !(is.na(pctblkpopinterp)), !(is.na(pctasianpopinterp)), !(is.na(pctlatinopopinterp)),
         !(is.na(medinc_cpi)), !(is.na(pctlocalgovworker_100)), !(is.na(pctrentersinterp)),
         !(is.na(pctover65)), !(is.na(pctcollegegradinterp)), !(is.na(logpop)))
```

```r
# create dge variable used in regression

fin_dge <-fin %>% filter(dgepercap_cpi != 0)

fin_dge_tab <- tibble(
  Variable = "Direct General Expenditure per Capita",
  Obs = nrow(fin_dge),
  Mean = mean(fin_dge$dgepercap_cpi, na.rm = T),
  SD = sd(fin_dge$dgepercap_cpi, na.rm = T),
  Min = min(fin_dge$dgepercap_cpi, na.rm = T),
  Max = max(fin_dge$dgepercap_cpi, na.rm = T)
)

print(fin_dge_tab)
```

```
# A tibble: 1 x 6
  Variable                                Obs  Mean    SD      Min   Max
  <chr>                                 <int> <dbl> <dbl>    <dbl> <dbl>
1 Direct General Expenditure per Capita 73119 0.907  3.09 0.000604  307.
```

```r
# now we have 73,119 observations compared to 13,742

nrow(fin_seg)
```

```
[1] 324178
```

```r
# number of missing seg indexes before imputation: 282334

# number missing now: 222957
282334 - 222957
```

```
[1] 59377
```

```r
73119-13742
```

```
[1] 59377
```

```r
# we were able to increase sample size by 59,377

miss_var_summary(complete(imp_2_fs))
```

```
# A tibble: 17 x 3
   variable              n_miss pct_miss
   <chr>                  <int>    <dbl>
 1 medinc_cpi            228903     75.8
 2 pctrentersinterp      228880     75.8
 3 diversityinterp       228878     75.8
 4 pctblkpopinterp       228878     75.8
 5 pctasianpopinterp     228878     75.8
 6 pctlatinopopinterp    228878     75.8
 7 pctlocalgovworker_100 228878     75.8
 8 pctcollegegradinterp  228878     75.8
 9 chng5pctblk           228878     75.8
10 chng5pctlatino        228878     75.8
11 chng5pctasian         228878     75.8
12 pctover65             228842     75.8
13 ideology_fill         227232     75.2
```

```
14 H_citytract_NHW_i     222957     73.8
15 dgepercap_cpi              0      0
16 logpop                     0      0
17 geo_id2                    0      0
```

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

Trounstine, Jessica. 2016. "Segregation and Inequality in Public Goods: SEGREGATION AND INEQUALITY IN PUBLIC GOODS." *American Journal of Political Science* 60 (3): 709–25. https://doi.org/10.1111/ajps.12227.

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	genrevown
	(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