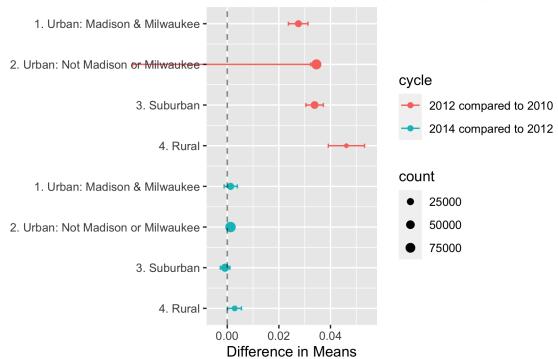
# Political Donor Polarization

Table 1: Bootstrapped difference-in-means test with 1,000 replications comparing mean partisanship by geographic category.

Geographic Category	Election Year	Diff.	CI	p
1. Urban: Madison & Milwaukee	2012 compared to	0.02757	0.02368-0.03127	<.001
	2010			
2. Urban: Not Madison or	2012 compared to	0.03453	0.03231-0.0367	<.001
Milwaukee	2010			
3. Suburban	2012 compared to	0.03384	0.03046-0.03722	<.001
	2010			
4. Rural	2012 compared to	0.04616	0.03915-0.05317	<.001
	2010			
1. Urban: Madison & Milwaukee	2014 compared to	0.00127	-0.00121-0.00392	0.294
	2012			
2. Urban: Not Madison or	2014 compared to	0.00126	0.00016-0.00241	0.03
Milwaukee	2012			
3. Suburban	2014 compared to	-0.00086	-0.0027-0.00104	0.376
	2012			
4. Rural	2014 compared to	0.00288	7e-05-0.00548	0.044
	2012			

## Saving  $6.5 \times 4.5$  in image





I grouped the donors according the four geographic categories to run the same difference-in-means test. The summary statistics tells a story that largely agrees with the results for the statewide analysis in Table 2; Wisconsin donors significantly polarized in the 2012 election cycle across both metropolitan and nonmetropolitan areas and remained that way come the 2014 election cycle. These results may spark the question: should we consider donor geography when looking at polarization? The answer may be rooted in what Cramer describes as "rural consciousness," or the strong sense of identity that the rural Wisconsinites felt alongside resentment towards the two main cities in a rising right-wing populist movement. The people outside of Madison and Milwaukee resonated with Scott Walker's appeal to their sense of distributive power injustice which was reflected in Act 10's attack on public employee unions. Indeed we can look at rural Wisconsin as well as cities excluding Madison and Milwaukee, which encompass the majority of Wisconsin's population. These two geographic categories had the greatest increase in polarization in both election cycles and were significant in both years. This confirms continuing support for Scott Walker and reflects the rural consciousness that continued to grow even after the 2012 election.

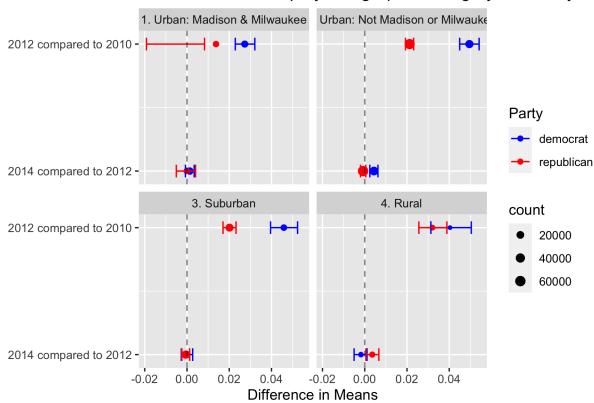
Table 2: Bootstrapped difference-in-means test with 1,000 replications comparing mean partisanship by geographic category.

Geographic Category	Party	Election Year	Diff.	CI	p
1. Urban: Madison &	democrat	2012 compared to	0.02734	0.02287-	<.001
Milwaukee		2010		0.03211	
2. Urban: Not Madison or	democrat	2012 compared to	0.04954	0.04495-	<.001
Milwaukee		2010		0.05416	
3. Suburban	democrat	2012 compared to	0.04586	0.03958-	<.001
		2010		0.05236	
4. Rural	democrat	2012 compared to	0.04037	0.03131-	<.001
		2010		0.05044	
1. Urban: Madison &	democrat	2014 compared to	0.00135	-0.00073-	0.22
Milwaukee		2012		0.00342	
2. Urban: Not Madison or	democrat	2014 compared to	0.00436	0.0024-0.00624	<.001
Milwaukee		2012			
3. Suburban	democrat	2014 compared to	-	-0.00269-	0.944
		2012	0.00005	0.00269	
4. Rural	democrat	2014 compared to	-	-0.00504-	0.236
		2012	0.00180	0.00106	
1. Urban: Madison &	republican	2012 compared to	0.01374	0.00833-0.0192	<.001
Milwaukee		2010			
2. Urban: Not Madison or	republican	2012 compared to	0.02125	0.0193-0.02315	<.001
Milwaukee		2010			
3. Suburban	republican	2012 compared to	0.02013	0.01706-	<.001
		2010		0.02323	
4. Rural	republican	2012 compared to	0.03207	0.02562-	<.001
		2010		0.03889	
1. Urban: Madison &	republican	2014 compared to	-	-0.00505-	0.984
Milwaukee		2012	0.00015	0.00406	

Geographic Category	Party	Election Year	Diff.	CI	p
2. Urban: Not Madison or	republican	2014 compared to	-	-0.00201-	0.22
Milwaukee		2012	0.00078	0.00046	
3. Suburban	republican	2014 compared to	-	-0.00246-	0.52
		2012	0.00059	0.00126	
4. Rural	republican	2014 compared to	0.00356	0.00054-	0.018
		2012		0.00668	

## Saving  $6.5 \times 4.5$  in image

## Difference in Mean Partisanship by Geographic Category and Party



To further analyze the partisan trends between Democrats and Republicans, I ran the same bootstrapping test for both parties in each of the geographic categories. In the 2012 compared to 2010 cycle, both parties had a significant mean difference in partisanship across the entire state, with Democrats consistently increasing their partisanship compared to Republicans. This aligns with the massive push to replace Governor Walker in the 2012 recall elections. Interestingly, despite the efforts among Democratic donors, the outcome of the election was not in their favor.

We can then move to note that in the 2014 to 2012 cycle, the Urban excluding Madison and Milwaukee and the Rural categories still had significant differences in partisanship. With this in mind, running the bootstrapping test allows us to see if this was true across both parties in these regions. The results of the test show that this was not the case. Somewhat unsurprisingly, only the Republican donors had a significant difference in partisanship from 2012 to 2014. This can possibly be linked to the growing "rural consciousness" that rural Republicans felt as they continued to identify with Scott Walker's ideas. On the other hand, in urban Wisconsin outside of the two major cities, it was Democratic donors that had a super significant difference in partisanship in 2014 while Republican donors remained unchanged...

Extracting key cities from the geographic category '2. Urban. Not Madison or Milwaukee'

Data taken from https://www.unitedstateszipcodes.org/wi/

## Comparing Old and New Donors (for a given election year)

Table 3: Bootstrapped difference-in-means test with 1,000 replications comparing mean partisanship of new versus old donors.

Election Year	Diff.	CI	p
2012	0.02277	0.02093-0.02477	<.001
2014	0.00708	0.00606-0.00809	<.001

```
## 'summarise()' has grouped output by 'election_year', 'geo_category'. You can override using the '.groups'
## 'summarise()' has grouped output by 'election_year'. You can override using the '.groups' argument.

## Joining, by = c("election_year", "geo_category")

## 'summarise()' has grouped output by 'election_year', 'geo_category'. You can override using the '.groups'
## 'summarise()' has grouped output by 'election_year'. You can override using the '.groups' argument.

## Joining, by = c("election_year", "party_bin")

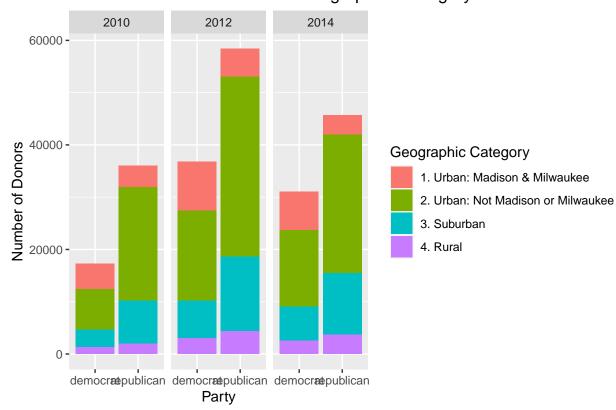
## Joining, by = c("election_year", "geo_category")
```

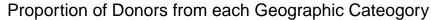
Table 4: Number of Donors, Proportion of Donations, and Percentage of Donors from each Geographic Category per Year

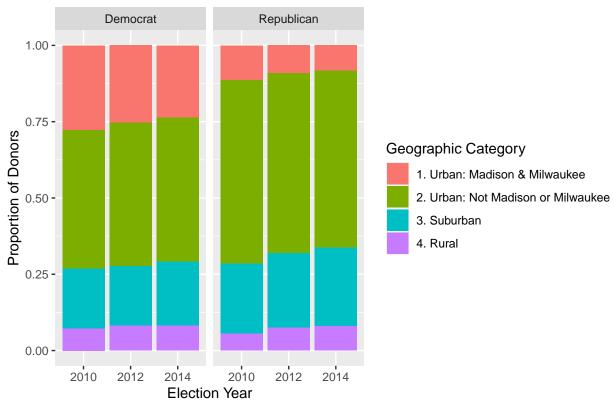
						% of yearly	
Election	Geographic	Democratic	Republican	% Dem	% Rep	Dem	% of yearly
Year	Cateogory	Donors	Donors	donations	donations	donors	Rep donors
2010	1. Urban:	4790	4118	0.5588885	0.4411115	0.2778583	0.1143254
	Madison &						
	Milwaukee						
2010	2. Urban: Not	7839	21643	0.1782203	0.8217797	0.4547248	0.6008606
	Madison or						
	Milwaukee						
2010	3. Suburban	3366	8288	0.2887292	0.7112708	0.1952549	0.2300944
2010	4. Rural	1244	1971	0.3682188	0.6317812	0.0721620	0.0547196
2012	1. Urban:	9294	5282	0.4372746	0.5627254	0.2526917	0.0904777
	Madison &						
	Milwaukee						
2012	2. Urban: Not	17291	34427	0.2616590	0.7383410	0.4701196	0.5897155
	Madison or						
	Milwaukee						
2012	3. Suburban	7215	14317	0.2648979	0.7351021	0.1961664	0.2452423
2012	4. Rural	2980	4353	0.3257401	0.6742599	0.0810223	0.0745645

						% of yearly	
Election	Geographic	Democratic	Republican	% Dem	% Rep	Dem	% of yearly
Year	Cateogory	Donors	Donors	donations	donations	donors	Rep donors
2014	1. Urban:	7373	3758	0.6360548	0.3639452	0.2373869	0.0822032
	Madison &						
	Milwaukee						
2014	2. Urban: Not	14623	26515	0.2661293	0.7338707	0.4708136	0.5799939
	Madison or						
	Milwaukee						
2014	3. Suburban	6552	11796	0.2735117	0.7264883	0.2109533	0.2580278
2014	4. Rural	2511	3647	0.3036583	0.6963417	0.0808461	0.0797751

## Number of Donors from each Geographic Cateogory







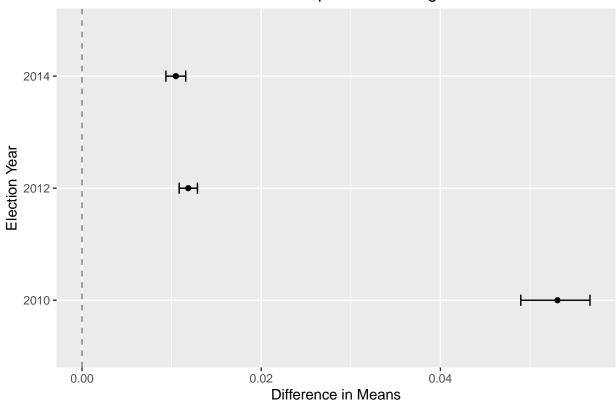
The first plot shows the number of donors in each geographic category by party and year, while the second graph breaks it down by percentages to see where donors are coming from. It is obvious that the divisive election of 2012 was reflected in a huge influx of donors from both parties. Looking at the proportions, we see that the distribution of donors across geographic categories remained largely consistent across election years. Republican donors came from predominately the non-Madison-or-Milwaukee urban category, while the Democratic party was dominated by the two urban regions.

Use \$200 cutoff to compare small and large donors

Table 5: Bootstrapped difference-in-means test with 1,000 replications comparing mean partisanship of small versus big donors.

Diff.	CI	p
0.05306	0.04897-0.05669	<.001
0.01185	0.01084-0.01288	<.001
0.01047	0.00936-0.01157	<.001
	0.05306 0.01185	0.01185 0.01084-0.01288

## Difference in Mean Partisanship between Large and Small Donors



From the results, small donors are significantly more polarized compared to big donors in all election years.

Different Urban/Rural Classifications

*Urban Inflence Codes (2013)* 

From https://www.ugpti.org/resources/reports/downloads/dp-207.pdf

"The Economic Research Service uses metropolitan, micropolitan, and non-core designations; population; and proximity to large urban areas to classify counties using its Urban Influence Code system. Micropolitan Statistical Areas are similar to Metropolitan Areas with the exception that the core urban area must have at least 10,000 residents. Metropolitan and Micropolitan Statistical Areas are jointly referred to as Core Based Statistical Areas. The Urban Influence system is intended to capture the role of urban areas and access on economic opportunity."

Using Urban Influence Codes might be an attractive option because it aims to classify geography by access to economic opportunity, which links to the rural resentment felt by nonmetropolitan Wisconsinites. Also the finer distinctions between nonmetro areas might be useful to separate and look at.

Table 6: Urban Influence Codes

Geographic	
Cateogry	Description
1 Metropolitan	In large metro area of 1+ million residents
2 Metropolitan	In small metro area of less than 1 million residents
3	Micropolitan area adjacent to large metro area
Nonmetropolitan	
4	Noncore adjacent to large metro area
Nonmetropolitan	
5	Micropolitan area adjacent to small metro area
Nonmetropolitan	
6	Noncore adjacent to small metro area and contains a town of at least 2,500 residents
Nonmetropolitan	
7	Noncore adjacent to small metro area and does not contain a town of at least 2,500
Nonmetropolitan	residents
8	Micropolitan area not adjacent to a metro area
Nonmetropolitan	

Geographic	
Cateogry	Description
9	Noncore adjacent to micro area and contains a town of at least 2,500 residents
Nonmetropolitan	
10	Noncore adjacent to micro area and does not contain a town of at least 2,500
Nonmetropolitan	residents
11	Noncore not adjacent to metro or micro area and contains a town of at least 2,500
Nonmetropolitan	residents
12	Noncore not adjacent to metro or micro area and does not contain a town of at least
Nonmetropolitan	2,500 residents

I decided to recode the donors by UIC codes similarly to the RUCC categories: 2 urban, one suburban, and one rural category. I summarized the donors in the table below.

```
## 'summarise()' has grouped output by 'election_year', 'geo_category'. You can override using the '.groups'
## 'summarise()' has grouped output by 'election_year'. You can override using the '.groups' argument.

## Joining, by = c("election_year", "geo_category")

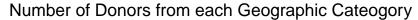
## 'summarise()' has grouped output by 'election_year', 'geo_category'. You can override using the '.groups'
## 'summarise()' has grouped output by 'election_year'. You can override using the '.groups' argument.

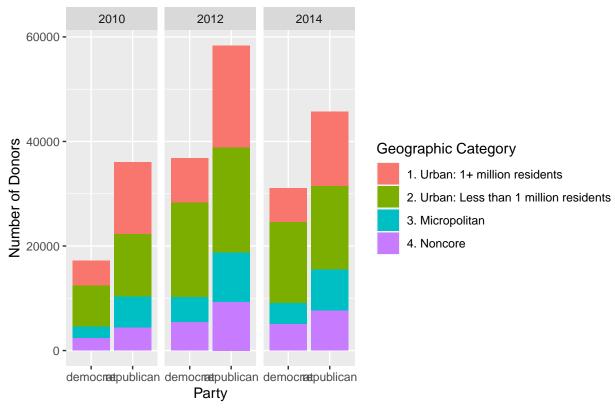
## Joining, by = c("election_year", "party_bin")

## Joining, by = c("election_year", "geo_category")
```

Table 7: Number of Donors, Proportion of Donations, and Percentage of Donors from each Geographic Category per Year

					% of yearly	
Election	Geographic	Democrati	icRepublica	n% Dem % Rep	Dem	% of yearly
Year	Cateogry	Donors	Donors	donations donations	donors	Rep donors
2010	1. Urban: 1+	4871	13792	0.1859478 0.8140522	0.2825570	0.3828984
	million residents					
2010	2. Urban: Less than	7758	11969	0.4295204 0.5704796	0.4500261	0.3322876
	1 million residents					
2010	3. Micropolitan	2230	5864	0.2794214 0.7205786	0.1293579	0.1627984
2010	4. Noncore	2380	4395	0.3397248 0.6602752	0.1380591	0.1220155
2012	1. Urban: 1+	8442	19592	0.2422605 0.7577395	0.2295269	0.3356001
	million residents					
2012	2. Urban: Less than	18143	20117	0.3800353 0.6199647	0.4932844	0.3445931
	1 million residents					
2012	3. Micropolitan	4813	9387	0.2628468 0.7371532	0.1308592	0.1607941
2012	4. Noncore	5382	9283	0.2968777 0.7031223	0.1463295	0.1590127
2014	1. Urban: 1+	6449	14214	0.2744927 0.7255073	0.2076371	0.3109196
	million residents					
2014	2. Urban: Less than	15547	16059	0.4912612 0.5087388	0.5005634	0.3512775
	1 million residents					
2014	3. Micropolitan	4023	7867	0.2453364 0.7546636	0.1295277	0.1720842
2014	4. Noncore	5040	7576	0.3186539 0.6813461	0.1622718	0.1657188





The image looks very similar to the RUCC classification, except with less suburban and more rural-classified donors. I ran the test on all the categories without grouping.

Table 8: Bootstrapped difference-in-means test with 1,000 replications comparing mean partisanship by geographic category.

Geographic Category	Election Year	Diff.	CI	p
1	2012 compared to 2010	0.02489	0.02233-0.02735	<.001
2	2012 compared to 2010	0.04077	0.0379-0.04347	<.001
3	2012 compared to 2010	0.02325	0.01899-0.02784	<.001
4	2012 compared to 2010	0.02887	0.01716-0.04141	<.001
5	2012 compared to 2010	0.04352	0.03635-0.05035	<.001
6	2012 compared to 2010	0.04227	0.03647-0.04872	<.001
7	2012 compared to 2010	0.03622	0.0201-0.05263	<.001
8	2012 compared to 2010	0.04899	-0.02675-0.15812	0.342
9	2012 compared to 2010	0.06225	0.04641-0.07831	<.001
11	2012 compared to 2010	0.01753	0.00388-0.03275	0.01

Geographic Category	Election Year	Diff.	CI	р
12	2012 compared to 2010	0.04548	0.03105-0.06354	<.001
1	2014 compared to 2012	0.00470	0.00313-0.00627	<.001
2	2014 compared to 2012	-0.00092	-0.00241-0.00052	0.232
3	2014 compared to 2012	0.00262	0.00013-0.00503	0.044
4	2014 compared to 2012	-0.00409	-0.00954-0.00117	0.132
5	2014 compared to 2012	-0.00044	-0.00453-0.00372	0.82
6	2014 compared to 2012	-0.00254	-0.00541-0.00023	0.088
7	2014 compared to 2012	0.00281	-0.00707-0.01104	0.506
8	2014 compared to 2012	0.01273	-0.01362-0.04097	0.396
9	2014 compared to 2012	0.00483	-0.00059-0.00982	0.078
11	2014 compared to 2012	0.00195	-0.00609-0.01055	0.646
12	2014 compared to 2012	0.00214	-0.00183-0.00608	0.29

Table 9: Bootstrapped difference-in-means test with 1,000 replications comparing mean partisanship by geographic category.

Geographic Category	Election Year	Diff.	CI	p
1. Urban: 1+ million residents	2012 compared to	0.02489	0.02233-0.02735	<.001
	2010			
2. Urban: Less than 1 million residents	2012 compared to	0.04077	0.0379-0.04347	<.001
	2010			
3. Micropolitan	2012 compared to	0.03169	0.0277-0.0356	<.001
	2010			
4. Noncore	2012 compared to	0.04221	0.03717-0.04699	<.001
	2010			
1. Urban: 1+ million residents	2014 compared to	0.00470	0.00313-0.00627	<.001
	2012			
2. Urban: Less than 1 million residents	2014 compared to	-0.00092	-0.00241-0.00052	0.232
	2012			
3. Micropolitan	2014 compared to	0.00104	-0.00116-0.00322	0.354
	2012			

Geographic Category	Election Year	Diff.	CI	р
4. Noncore	2014 compared to	-0.00089	-0.00294-0.0011	0.42
	2012			

The difference-in-means test resulted in only the first urban category to be significant, which is different from what the RUCC data gave us (with both the 2nd urban category and rural significant). Finally, I decided to group into six categories based on adjacency to urban areas and ran the same test. Again, only the first category was significant for the 2014 election cycle.

Table 10: Bootstrapped difference-in-means test with 1,000 replications comparing mean partisanship by geographic category.

Geographic Category	Election Year	Diff.	CI	p
1. Urban: 1+ million residents	2012 compared to	0.02489	0.02233-	<.001
	2010		0.02735	
2. Urban: Less than 1 million residents	2012 compared to	0.04077	0.0379-0.04347	<.001
	2010			
3. Micropolitan: Adjacent to an urban area	2012 compared to	0.03173	0.02785-	<.001
	2010		0.03589	
4. Micropolitan: Not adjacent to an urban	2012 compared to	0.04575	-0.03129-	0.318
area	2010		0.1419	
5. Noncore: Adjacent to a metro area	2012 compared to	0.04303	0.03788-	<.001
	2010		0.04805	
6. Noncore: Not Adjacent a metro area	2012 compared to	0.03552	0.02443-0.0473	<.001
	2010			
1. Urban: 1+ million residents	2014 compared to	0.00470	0.00313-	<.001
	2012		0.00627	
2. Urban: Less than 1 million residents	2014 compared to	-0.00092	-0.00241-	0.232
	2012		0.00052	
3. Micropolitan: Adjacent to an urban area	2014 compared to	0.00097	-0.00127-	0.406
	2012		0.00313	

Geographic Category	Election Year	Diff.	CI	p
4. Micropolitan: Not adjacent to an urban	2014 compared to	0.01311	-0.01696-	0.386
area	2012		0.04348	
5. Noncore: Adjacent to a metro area	2014 compared to	-0.00133	-0.00373-0.001	0.286
	2012			
6. Noncore: Not Adjacent a metro area	2014 compared to	0.00152	-0.0023-	0.466
	2012		0.00537	

#### CDC's 2013 NCHS Urban-Rural Classification Scheme for Counties

From https://www.cdc.gov/nchs/data/series/sr\_02/sr02\_166.pdf

"A key feature of the NCHS urban-rural scheme, which makes it particularly well-suited for health analyses, is that it separates counties within large metropolitan areas (1 million or more population) into two categories: large "central" metro (akin to inner cities) and large "fringe" metro (akin to suburbs). This is an important feature of the NCHS urban-rural scheme because for a number of health measures, residents of large fringe metro areas fare substantially better than residents of other urbanization levels. For these measures, residents of the inner cities and suburbs of large metropolitan areas must be differentiated to obtain an accurate characterization of health disparities across the full urban-rural spectrum."

The NCHS classification scheme primarily uses population as its measure of urbanization, and it tries to capture health (quality of life?) is that urban areas are broken up more, with even more specificity between a "large central metro" and a "large fringe metro." I thought that this turned out useful later. Also I didn't think regrouping was necessary since the six categories seemed pretty clear.

Table 11: NCHS Urban-Rural Scheme

Urbaniza	ation
Level	Classification Rules
1.	Counties in MSAs of 1 million or more population that: 1) Contain the entire population of
Large	the largest principal city of the MSA, or 2) Have their entire population contained in the
Central	largest principal city of the MSA, or 3) Contain at least 250,000 inhabitants of any principal
Metro	city of the MSA
2.	Counties in MSAs of 1 million or more population that did not qualify as large central metro
Large	counties
Fringe	
Metro	
3.	Counties in MSAs of populations of 250,000–999,999
Medium	
Metro	
4.	Counties in MSAs of populations less than 250,000
Small	
Metro	

Urbanization

#### Level Classification Rules

5. Counties in micropolitan statistical areas

#### Micropolitan

6. Nonmetropolitan counties that did not qualify as micropolitan

#### Noncore

```
## 'summarise()' has grouped output by 'election_year', 'geo_category'. You can override using the '.groups'
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## Joining, by = c("election_year", "geo_category")

## 'summarise()' has grouped output by 'election_year', 'geo_category'. You can override using the '.groups'
## 'summarise()' has grouped output by 'election_year'. You can override using the '.groups' argument.

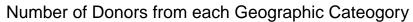
## Joining, by = c("election_year", "party_bin")

## Joining, by = c("election_year", "geo_category")
```

Table 12: Number of Donors, Proportion of Donations, and Percentage of Donors from each Geographic Category per Year

Election	Geographic	Democratic I	Republican	% Dem	% Rep	% of yearly	% of yearly
Year	Cateogry	Donors	Donors	donations	donations	Dem donors	Rep donors
2010	1. Large	2796	4022	0.5115446	0.4884554	0.1621904	0.1116602
	Central						
	Metro						
2010	2. Large	2075	9770	0.1034020	0.8965980	0.1203666	0.2712382
	Fringe						
	Metro						
2010	3. Medium	3976	3659	0.5225614	0.4774386	0.2306398	0.1015825
	Metro						
2010	4. Small	3782	8310	0.3240419	0.6759581	0.2193863	0.2307052
	Metro						

Election	Geographic	Democratic 1	Republican	% Dem	% Rep	% of yearly	% of yearly
Year	Cateogry	Donors	Donors	donations	donations	Dem donors	Rep donors
2010	5.	2230	5864	0.2794214	0.7205786	0.1293579	0.1627984
	Micropolitan						
2010	6. Noncore	2380	4395	0.3397248	0.6602752	0.1380591	0.1220155
2012	1. Large	4111	4960	0.3593131	0.6406869	0.1117727	0.0849621
	Central						
	Metro						
2012	2. Large	4331	14632	0.1821010	0.8178990	0.1177542	0.2506381
	Fringe						
	Metro						
2012	3. Medium	9846	6309	0.4875038	0.5124962	0.2676998	0.1080697
	Metro						
2012	4. Small	8297	13808	0.2732979	0.7267021	0.2255846	0.2365234
	Metro						
2012	5.	4813	9387	0.2628468	0.7371532	0.1308592	0.1607941
	Micropolitan						
2012	6. Noncore	5382	9283	0.2968777	0.7031223	0.1463295	0.1590127
2014	1. Large	3289	3573	0.4607893	0.5392107	0.1058952	0.0781564
	Central						
	Metro						
2014	2. Large	3160	10641	0.1783404	0.8216596	0.1017418	0.2327631
	Fringe						
	Metro						
2014	3. Medium	8374	5262	0.5740385	0.4259615	0.2696159	0.1151019
	Metro						
2014	4. Small	7173	10797	0.3166254	0.6833746	0.2309476	0.2361755
	Metro						
2014	5.	4023	7867	0.2453364	0.7546636	0.1295277	0.1720842
	Micropolitan						
2014	6. Noncore	5040	7576	0.3186539	0.6813461	0.1622718	0.1657188



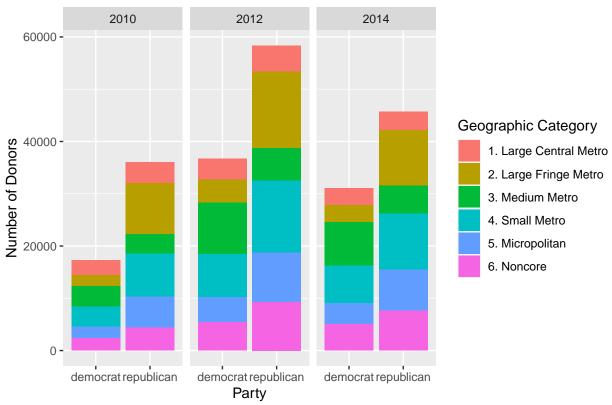


Table 13: Bootstrapped difference-in-means test with 1,000 replications comparing mean partianship by geographic category.

Geographic Category	Election Year	Diff.	CI	р
1. Large Central Metro	2012 compared to 2010	0.02168	0.01738-0.02596	<.001
2. Large Fringe Metro	2012 compared to 2010	0.02665	0.02354-0.0301	<.001
3. Medium Metro	2012 compared to 2010	0.04829	0.04328-0.05292	<.001
4. Small Metro	2012 compared to 2010	0.03639	0.0331-0.03996	<.001
5. Micropolitan	2012 compared to 2010	0.03165	0.02764-0.03597	<.001
6. Noncore	2012 compared to 2010	0.04219	0.03748-0.04716	<.001
1. Large Central Metro	2014 compared to 2012	0.00296	0.00023-0.00569	0.03
2. Large Fringe Metro	2014 compared to 2012	0.00553	0.0037-0.00736	<.001
3. Medium Metro	2014 compared to 2012	-0.00184	-0.0043-0.00064	0.128
4. Small Metro	2014 compared to 2012	-0.00029	-0.00216-0.00154	0.78
5. Micropolitan	2014 compared to 2012	0.00104	-0.00106-0.00312	0.36
6. Noncore	2014 compared to 2012	-0.00086	-0.00305-0.00131	0.414

I ran the same bootstrapping test on the donor data based on the NCHS scheme and saw that in 2014, both urban areas got significantly more polarized. This disagrees with the ruce scheme, which showed that Madison and Milwaukee did not get significantly more polarized in 2014. I decided to pull the cities from the "Large Fringe" group and found that they were a subset of the "2. Urban: Not Madison and Milwaukee" category.

The results of further testing by party are below:

Table 14: Bootstrapped difference-in-means test with 1,000 replications comparing mean partianship by geographic category.

Geographic Category	Party	Election Year	Diff.	CI	p
1. Large Central Metro	democrat	2012 compared to	0.02653	0.0208-0.03291	<.001
		2010			
2. Large Fringe Metro	democrat	2012 compared to	0.05834	0.04825-0.06895	<.001
		2010			

Geographic Category	Party	Election Year	Diff.	CI	р
3. Medium Metro	democrat	2012 compared to	0.03955	0.03444-0.04505	<.001
		2010			
4. Small Metro	democrat	2012 compared to	0.04310	0.03718-0.04948	<.001
		2010			
5. Micropolitan	democrat	2012 compared to	0.04262	0.03543-0.05026	<.001
		2010			
6. Noncore	democrat	2012 compared to	0.04626	0.0389-0.05397	<.001
		2010			
1. Large Central Metro	democrat	2014 compared to	0.00185	-0.00158-0.00512	0.26
		2012			
2. Large Fringe Metro	democrat	2014 compared to	0.01416	0.00934-0.01883	<.001
		2012			
3. Medium Metro	democrat	2014 compared to	0.00070	-0.00148-0.00286	0.518
		2012			
4. Small Metro	democrat	2014 compared to	0.00130	-0.00141-0.00393	0.336
		2012			
5. Micropolitan	democrat	2014 compared to	0.00141	-0.00159-0.00462	0.372
		2012			
6. Noncore	democrat	2014 compared to	-0.00238	-0.00509-0.00044	0.108
		2012			
1. Large Central Metro	republican	2012 compared to	0.00954	0.00525-0.01425	<.001
		2010			
2. Large Fringe Metro	republican	2012 compared to	0.01411	0.01152-0.01676	<.001
		2010			
3. Medium Metro	republican	2012 compared to	0.04315	0.03664-0.04941	<.001
		2010			
4. Small Metro	republican	2012 compared to	0.02344	0.02018-0.02692	<.001
		2010			
5. Micropolitan	republican	2012 compared to	0.01960	0.01587-0.02343	<.001
		2010			

Geographic Category	Party	Election Year	Diff.	CI	p
6. Noncore	republican	2012 compared to	0.02602	0.02145-0.03014	<.001
		2010			
1. Large Central Metro	republican	2014 compared to	0.00274	-0.00071-0.00613	0.114
		2012			
2. Large Fringe Metro	republican	2014 compared to	0.00242	0.00089-0.00395	0.002
		2012			
3. Medium Metro	republican	2014 compared to	-0.00545	-0.0095-0.00121	0.01
		2012			
4. Small Metro	republican	2014 compared to	-0.00183	-0.00392-0.00016	0.076
		2012			
5. Micropolitan	republican	2014 compared to	0.00157	-5e-04-0.00385	0.15
		2012			
6. Noncore	republican	2014 compared to	-0.00072	-0.00292-0.00134	0.524
		2012			

<sup>##</sup> Warning: Removed 1 rows containing missing values (geom\_errorbarh).

## Difference in Mean Partisanship by Geographic Category and Party



#### Rural-Urban Commuting Area Codes (RUCAs)

From https://depts.washington.edu/uwruca/index.php

"RUCAs, Rural-Urban Commuting Area Codes, are a new Census tract-based classification scheme that utilizes the standard Bureau of Census Urbanized Area and Urban Cluster definitions in combination with work commuting information to characterize all of the nation's Census tracts regarding their rural and urban status and relationships. In addition, a ZIP Code RUCA approximation was developed."

Documentation for variables: https://depts.washington.edu/uwruca/ruca-documentation.php UA=Urbanized Area UC=Urban Cluster

Table 15: Rural-Urban Commuting Area Codes

RUCA	
Code	Description
1	Metropolitan area core: primary flow within an Urbanized Area (UA)
2	Metropolitan area high commuting: primary flow 30% or more to a UA
3	Metropolitan area low commuting: primary flow 10% to 30% to a UA
4	Micropolitan* area core: primary flow within an Urban Cluster (UC) of 10,000 through
	49,999 (large UC)
5	Micropolitan* high commuting: primary flow 30% or more to a large UC
6	Micropolitan* low commuting: primary flow 10% to 30% to a large UC
7	Small town core: primary flow within an Urban Cluster of 2,500 through 9,999 (small UC)
8	Small town high commuting: primary flow 30% or more to a small UC
9	Small town low commuting: primary flow 10% through 29% to a small UC
10	Rural areas: primary flow to a tract outside a UA or UC (including self)

Each category had a couple of subcategories (7, 7.1, 7.2, etc) to further break down the categories but I simplified it just by taking the floor of the full code (everything rounds down).

Table 16: Bootstrapped difference-in-means test with 1,000 replications comparing mean partisanship by geographic category.

Geographic Category	Election Year	Diff.	CI	p
1	2012 compared to 2010	0.03481	0.0326-0.03706	<.001

Geographic Category	Election Year	Diff.	CI	р
2	2012 compared to 2010	0.03435	0.02949-0.03882	<.001
3	2012 compared to 2010	0.04381	0.0241-0.06418	<.001
4	2012 compared to 2010	0.02445	0.01978-0.02935	<.001
5	2012 compared to 2010	0.03794	0.02101-0.05562	<.001
6	2012 compared to 2010	0.03123	0.01354-0.05087	<.001
7	2012 compared to 2010	0.03672	0.03162-0.04207	<.001
8	2012 compared to 2010	0.06756	0.04518-0.09145	<.001
9	2012 compared to 2010	0.01166	0.00118-0.02443	0.034
10	2012 compared to 2010	0.03217	0.02744-0.0372	<.001
1	2014 compared to 2012	0.00017	-0.00107-0.00136	0.798
2	2014 compared to 2012	0.00117	-0.00132-0.00348	0.354
3	2014 compared to 2012	-0.00331	-0.01119-0.00412	0.386
4	2014 compared to 2012	0.00613	0.00327-0.00924	<.001
5	2014 compared to 2012	-0.00254	-0.01013-0.00471	0.478
6	2014 compared to 2012	-0.00141	-0.01078-0.00741	0.776
7	2014 compared to 2012	0.00405	0.00134-0.00691	<.001
8	2014 compared to 2012	0.00123	-0.00592-0.0087	0.74
9	2014 compared to 2012	0.00070	-0.00498-0.0068	0.794
10	2014 compared to 2012	-0.00247	-0.00489–3e-05	0.046

The Divided (But Not More Predictable) Electorate: A Machine Learning Analysis of Voting in American Presidential Election

https://preprints.apsanet.org/engage/api-gateway/apsa/assets/orp/resource/item/6050dba7df04091d6a7fb4ef/original/the-divided-but-not-more-predictable-electorate-a-machine-learning-analysis-of-voting-in-american-presidential-elections.pdf

- Demographics have not become more predictive of vote choice
  - When all variables are included and some sort of stepping is performed, demographics do not make
- Focus on 5 demographic markers: race, education, income, age, gender

Main method used: random forests to predict voting predictions, using data from five surveys - Also a logistic regression for voice choice as y-variable, and CART model to confirm results

General results: demographics alone is a bad predictor (65% ish or less)