Relationship between social capital and election results

Anisha Babu[1], Hyeonjin Cha[1], Diana DeWald[1], & Murat Kezer[1]

[1] University of Oregon

Author Note

Add complete departmental affiliations for each author here. Each new line herein must be indented, like this line. Enter author note here.

The authors made the following contributions. Anisha Babu: Conceptualization, Data Analysis, Writing - Original Draft Preparation, Writing - Review & Editing; Hyeonjin Cha: Conceptualization, Data Analysis, Writing - Original Draft Preparation, Writing - Review & Editing; Diana DeWald: Conceptualization, Data Analysis, Writing - Original Draft Preparation, Writing - Review & Editing; Murat Kezer: Conceptualization, Data Analysis, Writing - Original Draft Preparation, Writing - Review & Editing.

Abstract

One or two sentences providing a **basic introduction** to the field, comprehensible to a scientist in any discipline.

Two to three sentences of **more detailed background**, comprehensible to scientists in related disciplines.

One sentence clearly stating the **general problem** being addressed by this particular study.

One sentence summarizing the main result (with the words “**here we show**” or their equivalent).

Two or three sentences explaining what the **main result** reveals in direct comparison to what was thought to be the case previously, or how the main result adds to previous knowledge.

One or two sentences to put the results into a more **general context**.

Two or three sentences to provide a **broader perspective**, readily comprehensible to a scientist in any discipline.

Keywords: keywords

Word count: X

Relationship between social capital and election results

Introduction

Social science literature has extensively examined the relationship between social capital and politics (e.g. Morales & Guigni, 2016; Jottier & Heyndels, 2012; La Due Lake & Huckfeldt, 1998). However, relatively little is known on the impact of social capital election results.

Methods

We report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study.

Data

- County Presidential Election Returns 2000-2016 (MIT Election Data and Science Lab, 2018)
  - County level returns for presidential elections from 2000 to 2016
  - Election results across the years in one dataset & in tidy format
- The production of social capital in US counties (Rupasingha, Goetz, & Freshwater, 2006, with updates)
  - County level count of various establishments defined by NAICS code
  - Different variables measured across years; new dataset for each year

Data Preparation

Load data and clean names. We first load the datasets and clean the variable names.

Clean data.

Election data.

- We start with the election data as it is more comprehensive in terms of the number of counties. First, we select the variables of interests. Then, we select the election year (i.e., 2000, 2008, 2012, 2016) that we will match with social capital data.

- The name of the year variable is changed in a way that shows it is the year of election (so that it is not mixed with the same year variable in social capital data).

- We create new datasets for each presidential election we are interested in. These will be later merged with corresponding social capital data.

Social capital data.

- For each social capital dataset (i.e., 1997, 2005, 2009, 2014), we first add state code for some counties that do not readily contain that information. Then, we create two variables out of the area name such that we have different variables for county names and state codes.

- We select the relevant variables and clean the variable names.

- We create a year variable indicating when the data were collected.

- Finally, we reorder variables so that the order of the variables is the same across datasets. This will be useful when we want to merge social capital data across year so that we can get descriptive statistics for each year simultaneously and that we can visualize the changes across years in social capital.

Merge Datasets.

- First, we merge social capital data across years for reasons explained above, and call it `s_capital`.
- Next, we merge corresponding election and social capital data for 4 time points. **In doing so,** we keep the rows that exist in both election and social capital data. For instance, if we do not have the election information for a county, we do not include it in the merged dataset even if we have that county's social capital data. These datasets are called `df_year`. *Year* denotes the year of election. Also, we remove the duplicate variables (i.e., state and county names) and fix the names. We did not remove them earlier because we first wanted to merge the social capital data with all the variables.
- Finally, we merge all election and social capital data in the same dataset (i.e., `df`). In addition, we created another dataset using `pivot_wider()` to have variables for the candidate votes per political party. Then, we removed the intermediate objects (i.e., all data frames except for `df` and `df_wide`).

Data analysis

```
##                bowl        civic          golf         relig        sport
## bowl     1.00000000  0.163331564  0.1843690062  1.754235e-01 -0.011262877
## civic    0.16333156  1.000000000  0.1658962995  2.547000e-01 -0.003264050
## golf     0.18436901  0.165896299  1.0000000000  3.491323e-01 -0.021985208
## relig    0.17542352  0.254699957  0.3491322736  1.000000e+00  0.002806421
## sport   -0.01126288 -0.003264050 -0.0219852075  2.806421e-03  1.000000000
## pol     -0.02966700  0.001966347 -0.0334108615 -9.423555e-05  0.012883481
## prof    -0.01392921  0.076733734 -0.0417492547 -3.323368e-02  0.021631055
## bus      0.09723730  0.140544743  0.1370127533  3.110755e-01 -0.020948989
```

```
## labor      0.01396846  0.127298046 -0.0318697416 -4.609051e-02  0.017101150
## respn      0.04573144  0.033975898  0.0008135967 -8.286148e-03 -0.004274877
## pvote      0.08361274  0.095880533  0.1007224264  4.908534e-02  0.028533722
## pop       -0.06101167 -0.070326839 -0.1026103152 -2.262784e-01  0.023425173
## nccs       0.22185326  0.347937372  0.2808439095  3.743616e-01  0.017981863
## assn       0.29451849  0.484150132  0.4950591900  9.183900e-01  0.023813113
## demmargin -0.09156467 -0.037419358 -0.1379312816 -3.337933e-01  0.024754801
##                     pol        prof         bus         labor        respn
## bowl      -2.966700e-02 -0.01392921  0.09723730  0.0139684639  0.0457314391
## civic      1.966347e-03  0.07673373  0.14054474  0.1272980463  0.0339758984
## golf      -3.341086e-02 -0.04174925  0.13701275 -0.0318697416  0.0008135967
## relig     -9.423555e-05 -0.03323368  0.31107552 -0.0460905051 -0.0082861484
## sport      1.288348e-02  0.02163105 -0.02094899  0.0171011497 -0.0042748774
## pol        1.000000e+00  0.20178507  0.08837989  0.0511035445 -0.0353395859
## prof       2.017851e-01  1.00000000  0.16314793  0.1102856692  0.0756318706
## bus        8.837989e-02  0.16314793  1.00000000 -0.0188081662 -0.1678024962
## labor      5.110354e-02  0.11028567 -0.01880817  1.0000000000  0.1920688496
## respn     -3.533959e-02  0.07563187 -0.16780250  0.1920688496  1.0000000000
## pvote      4.581321e-02  0.04152891  0.07735125 -0.0036691656  0.1131580514
## pop        4.668483e-02  0.08947146 -0.09489972  0.0586595869  0.1039281594
## nccs       8.661840e-02  0.13549486  0.32688972 -0.0002338711 -0.1209083839
## assn       6.319277e-02  0.09392249  0.47070855  0.0830621339  0.0133341334
## demmargin  8.501235e-02  0.18630848 -0.09135165  0.1315740835  0.0595954442
##                 pvote         pop         nccs        assn   demmargin
## bowl       0.083612738 -0.06101167  0.2218532641  0.29451849 -0.09156467
## civic      0.095880533 -0.07032684  0.3479373723  0.48415013 -0.03741936
## golf       0.100722426 -0.10261032  0.2808439095  0.49505919 -0.13793128
```

```
## relig      0.049085341 -0.22627840  0.3743615599  0.91838999 -0.33379330
## sport      0.028533722  0.02342517  0.0179818630  0.02381311  0.02475480
## pol        0.045813214  0.04668483  0.0866183961  0.06319277  0.08501235
## prof       0.041528912  0.08947146  0.1354948632  0.09392249  0.18630848
## bus        0.077351254 -0.09489972  0.3268897173  0.47070855 -0.09135165
## labor     -0.003669166  0.05865959 -0.0002338711  0.08306213  0.13157408
## respn      0.113158051  0.10392816 -0.1209083839  0.01333413  0.05959544
## pvote      1.000000000  0.02826091  0.2303456902  0.11604985  0.10013568
## pop        0.028260911  1.00000000 -0.0958799517 -0.19781990  0.35179190
## nccs       0.230345690 -0.09587995  1.0000000000  0.49110261 -0.06627689
## assn       0.116049854 -0.19781990  0.4911026061  1.00000000 -0.25818469
## demmargin  0.100135681  0.35179190 -0.0662768883 -0.25818469  1.00000000

##
## Call:
## lm(formula = demmargin ~ 1 + bowl + civic + golf + relig + sport +
##     pol + prof + bus + labor + pvote + respn + pop, data = df_anal_2016)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.90456 -0.18538 -0.04293  0.15323  1.21563
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -4.604e-01  4.802e-02  -9.588  < 2e-16 ***
## bowl        -2.034e-01  9.204e-02  -2.210   0.0272 *
## civic        6.436e-02  3.853e-02   1.671   0.0949 .
## golf        -4.419e-02  4.695e-02  -0.941   0.3467
```

```
## relig       -1.583e-01  1.110e-02 -14.253  < 2e-16 ***
## sport        1.861e-01  2.800e-01   0.665   0.5064
## pol          4.993e-01  2.240e-01   2.229   0.0259 *
## prof         1.165e+00  1.454e-01   8.011 1.60e-15 ***
## bus         -4.153e-02  4.610e-02  -0.901   0.3677
## labor        4.958e-01  9.433e-02   5.256 1.58e-07 ***
## pvote        3.632e-01  5.692e-02   6.381 2.02e-10 ***
## respn       -2.638e-02  4.800e-02  -0.550   0.5826
## pop          2.653e-07  1.607e-08  16.504  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.283 on 3102 degrees of freedom
## Multiple R-squared:  0.2362, Adjusted R-squared:  0.2333
## F-statistic: 79.94 on 12 and 3102 DF,  p-value: < 2.2e-16
```

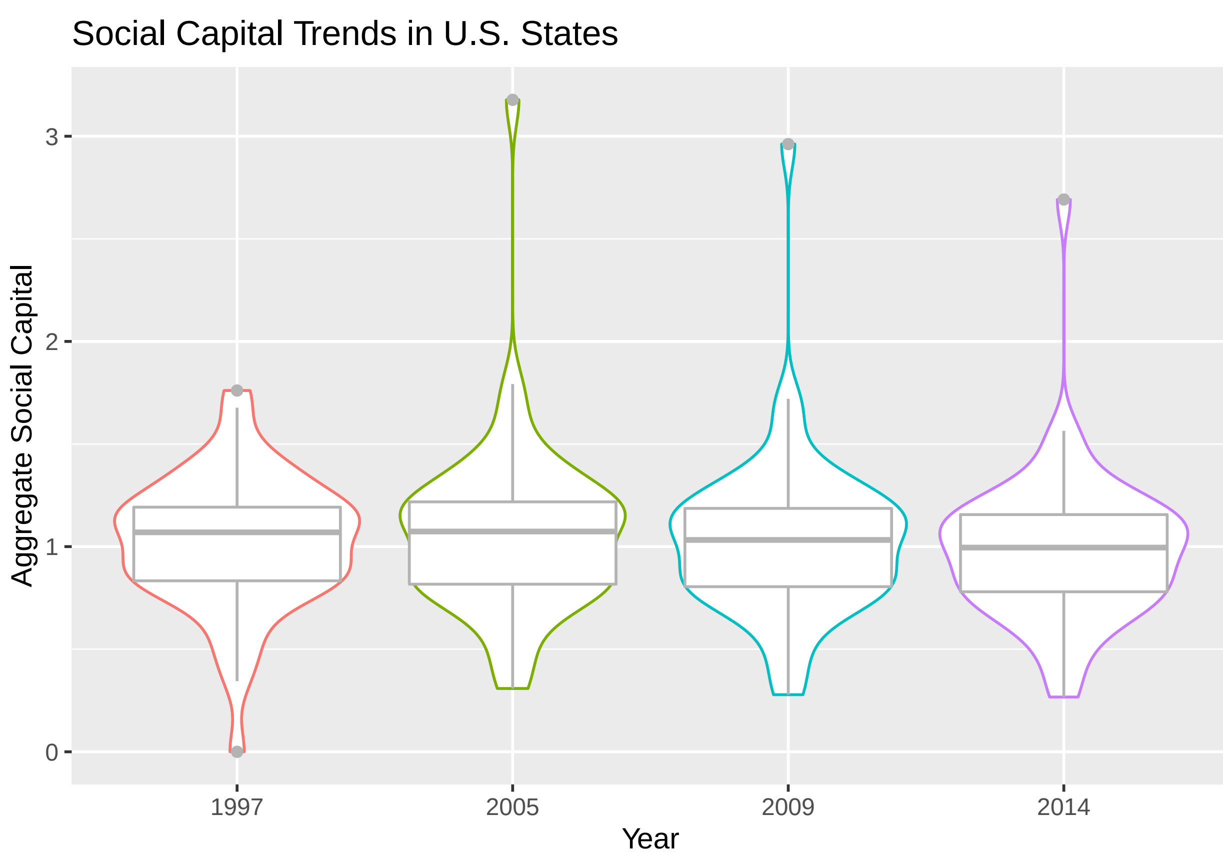
```
## # A tibble: 51 x 6
##    state_po     n m_totalvotes sd_totalvotes mean_pop   sd_pop
##    <chr>    <int>        <dbl>         <dbl>    <dbl>    <dbl>
##  1 AK           3        7036.          460.  103142.  170798.
##  2 AL         268       29724.        45394.   69187.  101303.
##  3 AR         300       14026.        21417.   37486.   53831.
##  4 AZ          60      145927.       330585.  394133.  889795.
##  5 CA         232      223051.       465584.  620980. 1387279.
##  6 CO         253       37272.        75235.   74612.  150559.
##  7 CT          32      196409.       151721.  437902.  347809.
##  8 DC           4      268195.        47994.  596734    43662.
##  9 DE          12      133073.        85452.  285361.  178905.
```

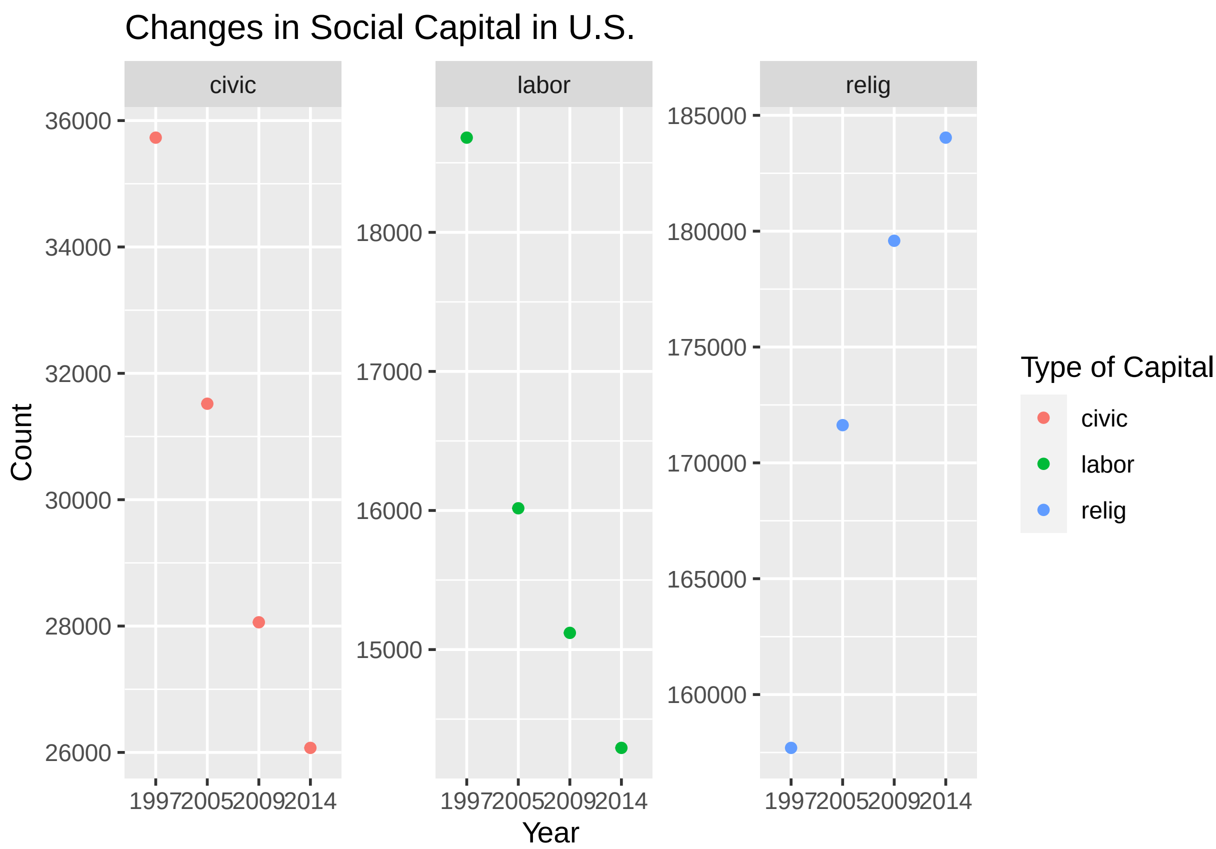
```
## 10 FL          267      118431.       173570.  260031.  415642.
## # ... with 41 more rows

## # A tibble: 13 x 5
## # Groups:   year_elctn [4]
##    year_elctn party     n m_candidatevotes sd_candidatevotes
##         <int> <fct> <int>            <dbl>             <dbl>
##  1       2000 Dem    3107           16218.            57150.
##  2       2000 Green  3107              NA                NA
##  3       2000 Rep    3107           16049.            38632.
##  4       2000 <NA>   3107             339.              954.
##  5       2008 Dem    3108           22157.            76972.
##  6       2008 Rep    3108           19167.            44840.
##  7       2008 <NA>   3108             577.             1848.
##  8       2012 Dem    3108           20974.            73998.
##  9       2012 Rep    3108           19409.            44596.
## 10       2012 <NA>   3108             838.             2952.
## 11       2016 Dem    3115           21071.            80496.
## 12       2016 Rep    3115           20160.            43157.
## 13       2016 <NA>   3115            2449.             7509.

## # A tibble: 36 x 7
## # Groups:   county, relig, civic, labor, democrat [36]
##    county    relig civic labor democrat republican voter_turnout
##    <chr>     <dbl> <dbl> <dbl>    <int>      <int>         <dbl>
##  1 Baker        11     5     1     2195       5618          64.8
##  2 Benton       50    13     3    19444      15825          63.3
##  3 Clackamas   184    32    13    76421      77539          62.8
```

```
##  4 Clatsop      35    12     7     8296       6950            60.8
##  5 Columbia     29     5     3    10331       9369            62.0
##  6 Coos         40     9     7    11610      15626            59.9
##  7 Crook        14     3     0     2474       5363            59.5
##  8 Curry        13     1     1     4090       6551            66.8
##  9 Deschutes    62    29     8    22061      32132            63.7
## 10 Douglas      77    12     4    14193      30294            59.6
## # ... with 26 more rows
```

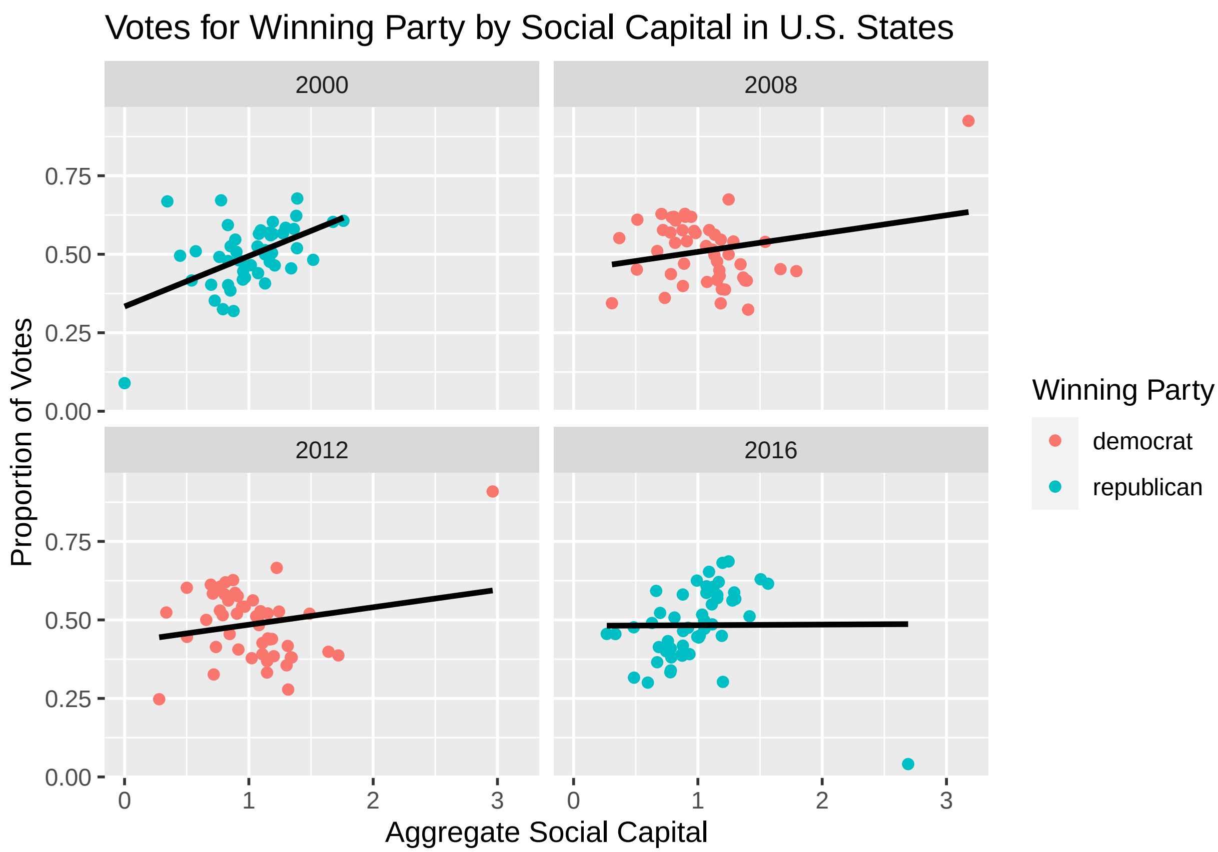
```
## # A tibble: 36 x 7
## # Groups:   county, relig, civic, labor, democrat [36]
##    county    relig civic labor democrat republican voter_turnout
##    <chr>     <dbl> <dbl> <dbl>    <int>      <int>         <dbl>
##  1 Baker        20     8     1     1797       6218          83.1
##  2 Benton       66    13     5    29193      13445          85.7
##  3 Clackamas   215    20    18   102095      88392          82.5
##  4 Clatsop      31    11     3     9252       8138          82.2
##  5 Columbia     26     4     2    10167      13217          82.2
##  6 Coos         53     7     5    10448      17865          82.2
##  7 Crook        20     3     0     2637       8511          83.2
##  8 Curry        15     1     0     4300       7212          84.3
##  9 Deschutes    92    22     7    42444      45692          84.1
## 10 Douglas      90     7     3    14096      34582          79.6
## # ... with 26 more rows
```

Characteristic	**exp(Beta)**	**95% CI**	**p-value**
bowl	-0.20	-0.38, -0.02	0.027
civic	0.06	-0.01, 0.14	0.095
golf	-0.04	-0.14, 0.05	0.3
relig	-0.16	-0.18, -0.14	<0.001
sport	0.19	-0.36, 0.74	0.5
pol	0.50	0.06, 0.94	0.026
prof	1.16	0.88, 1.45	<0.001
bus	-0.04	-0.13, 0.05	0.4
labor	0.50	0.31, 0.68	<0.001
pvote	0.36	0.25, 0.47	<0.001
respn	-0.03	-0.12, 0.07	0.6
pop	0.00	0.00, 0.00	<0.001

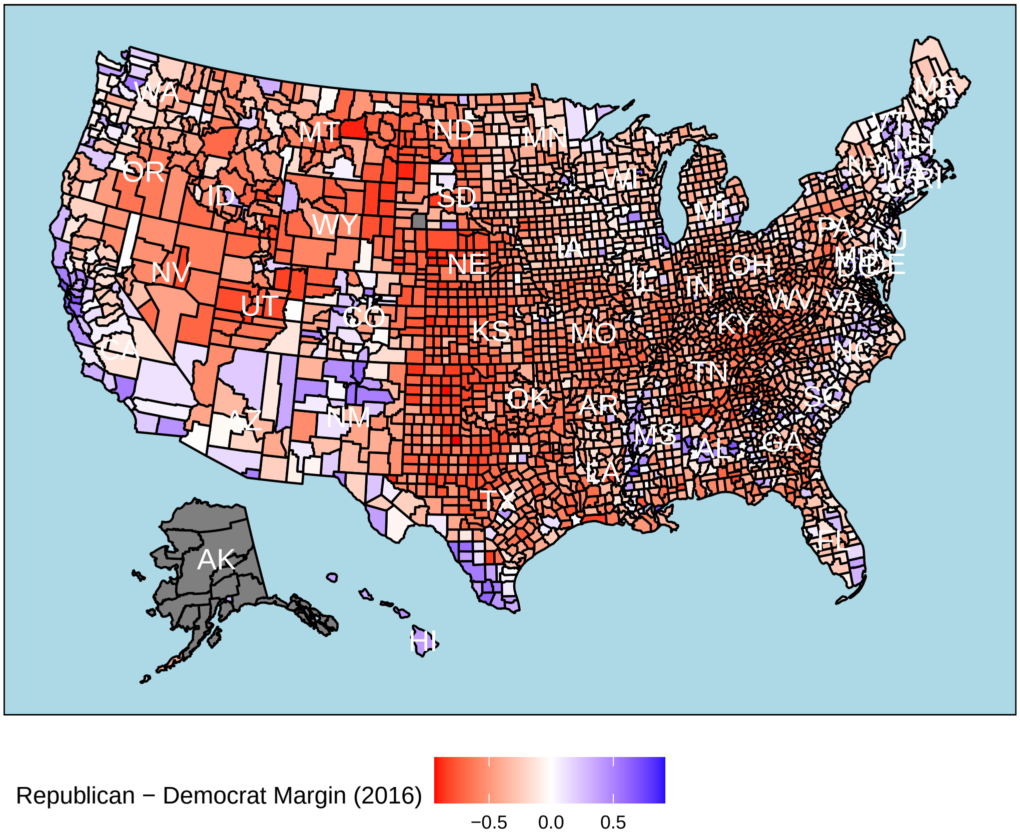


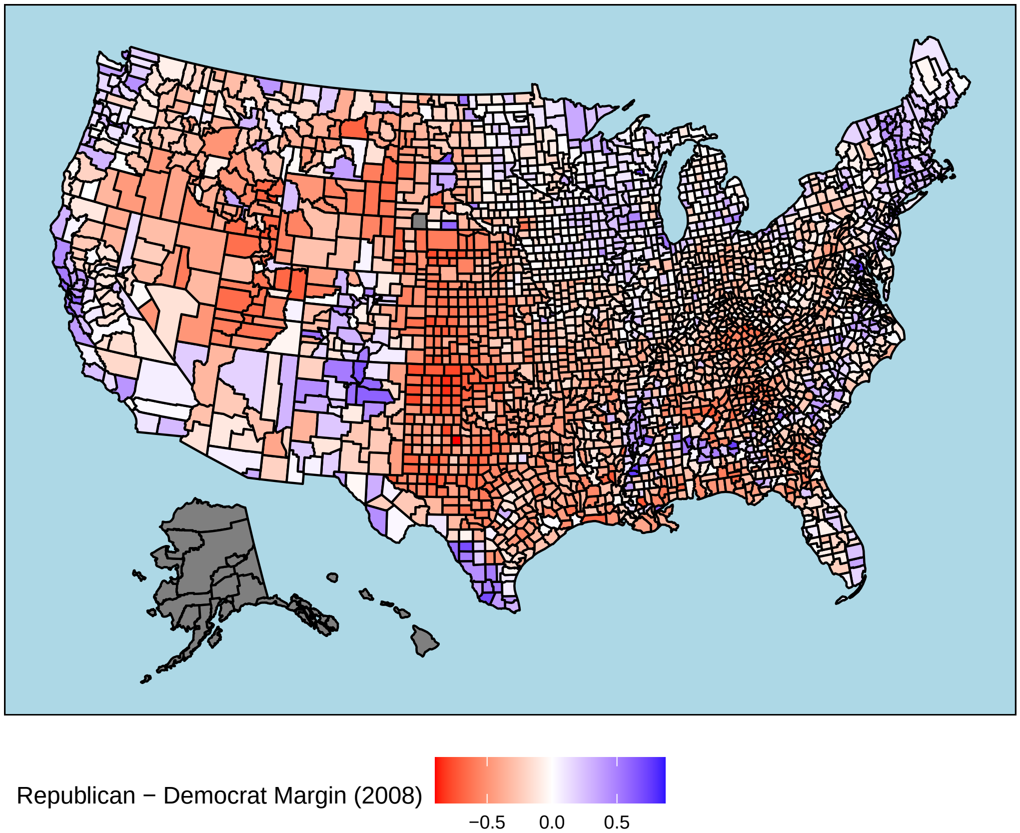


Changes in Social Capital in U.S.
civic
labor
relig
Count
36000
34000
32000
30000
28000
26000
18000
17000
16000
15000
185000
180000
175000
170000
165000
160000
1997200520092014
1997200520092014
1997200520092014
Year
Type of Capital
civic
labor
relig



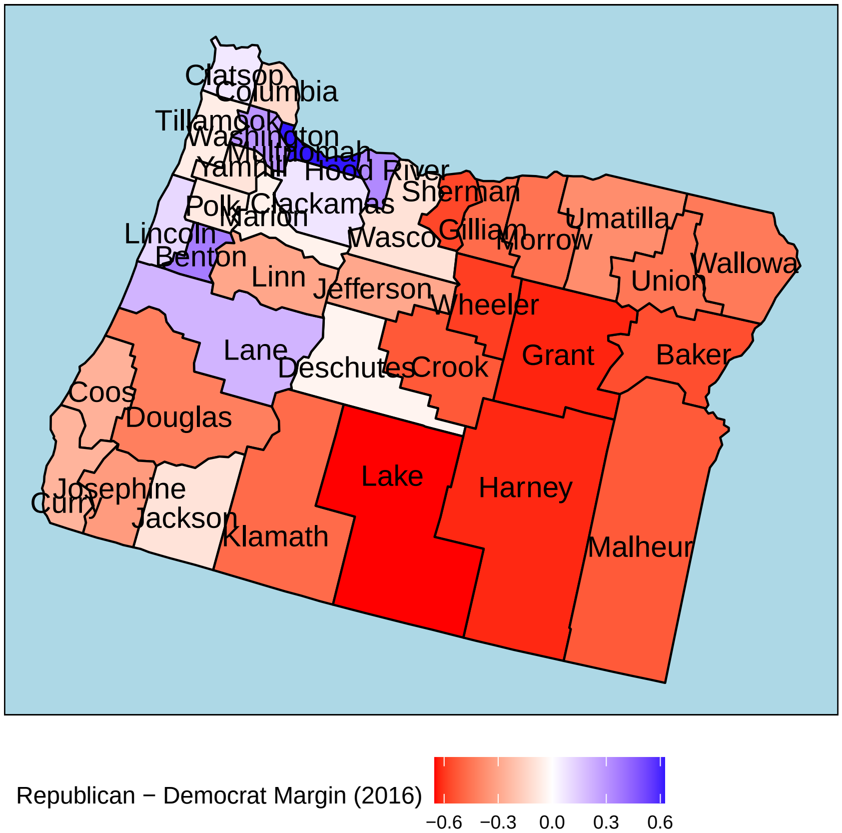

```
## Warning: package 'usmap' was built under R version 3.6.3
```

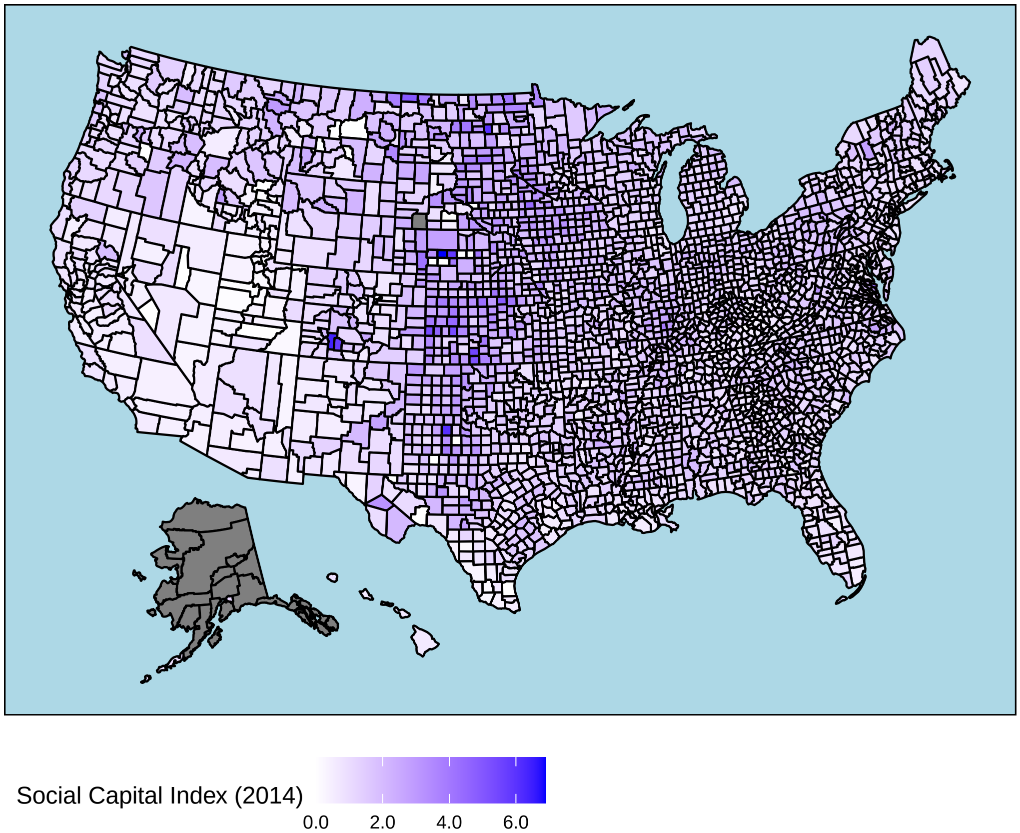

Republican − Democrat Margin (2016)
−0.5
0.0
0.5

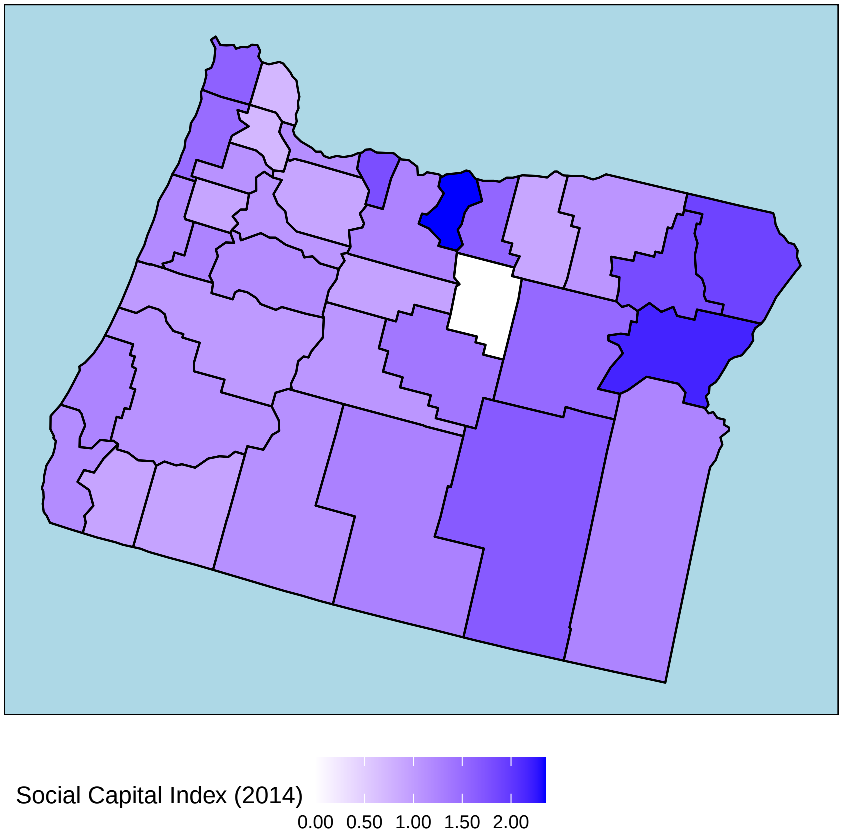



```
## [1] 2000 2008 2012 2016
```


2000
2008
2012
2016
NA
Republican − Democrat Margin (2016)
−0.5
0.0
0.5


Clatsop
Columbia
Tillamook
Washington
Multnomah
Yamhill
Hood River
Sherman
Polk
Clackamas
Marion
Lincoln
Benton
Wasco
Gilliam
Morrow
Umatilla
Union
Wallowa
Linn
Jefferson
Wheeler
Lane
Deschutes
Crook
Grant
Baker
Coos
Douglas
Lake
Harney
Josephine
Curry
Jackson
Klamath
Malheur
Republican − Democrat Margin (2016)
−0.6
−0.3
0.0
0.3
0.6


Social Capital Index (2014)
0.0
2.0
4.0
6.0



Results

Discussion

References

We used R [Version 3.6.1; 8] and the R-packages *broom* [**R-broom**], *dplyr* [Version 1.0.2; 14], *forcats* [Version 0.5.0; 9], *ggplot2* [Version 3.3.2; 10], *gtsummary* [**R-gtsummary**], *here* [Version 0.1; 6], *janitor* [Version 2.0.1; 4], *kableExtra* [**R-kableExtra**], *knitr* [Version 1.29; 16], *magrittr* [Version 1.5; 2], *papaja* [Version 0.1.0.9997; 1], *purrr* [Version 0.3.4; 5], *readr* [Version 1.3.1; 13], *rio* [Version 0.5.16; 3], *sjlabelled* [**R-sjlabelled**], *stringr* [Version 1.4.0; 11], *tibble* [Version 3.0.4; 7], *tidyr* [Version 1.1.2; 12], and *tidyverse* [Version 1.3.0; 15] for all our analyses.

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Table 1

*(#tab:descriptives tables)Table 1
 <i>A summary table for total votes and population by state.</i>*

		Total Votes		Population	
Sate	N	M	SD	M	SD
AK	3	7036	460	103142	170798
AL	268	29724	45394	69187	101303
AR	300	14026	21417	37486	53831
AZ	60	145927	330585	394133	889795
CA	232	223051	465584	620980	1387279
CO	253	37272	75235	74612	150559
CT	32	196409	151721	437902	347809
DC	4	268195	47994	596734	43662
DE	12	133073	85452	285361	178905
FL	267	118431	173570	260031	415642
GA	636	22857	51210	57121	120420
HI	4	107234	120109	355042	427919
IA	396	15153	26357	30298	50767
ID	176	14201	27837	33216	61206
IL	408	51632	207620	123712	528335
IN	368	28016	45752	68726	113969
KS	420	11068	32305	26466	70945
KY	480	14775	33166	35136	71897
LA	256	30265	40734	70853	97369
MA	56	218333	190389	462537	397378
MD	96	105686	125998	233911	281901
ME	64	44329	39811	81772	69901
MI	332	56520	122899	119512	266186
MN	348	32271	79906	59257	141434
MO	460	22676	57042	50644	121028

Table 2

*(#tab:descriptives tables)Table 2
 <i>A summary table for votes by candidate and year of election.</i>*

Year	Party	N	Mean Candidate Votes	SD Candidate Votes
2000	Dem	3107	16218	57150
2000	Green	3107	–	–
2000	Rep	3107	16049	38632
2000	–	3107	339	954
2008	Dem	3108	22157	76972
2008	Rep	3108	19167	44840
2008	–	3108	577	1848
2012	Dem	3108	20974	73998
2012	Rep	3108	19409	44596
2012	–	3108	838	2952
2016	Dem	3115	21071	80496
2016	Rep	3115	20160	43157
2016	–	3115	2449	7509

Note: N = total number of counties in the US reporting data.

Table 3

*(#tab:descriptives tables)Table 3
 <i>A summary table for the year 2000: Selected social capital and voting behavior in Oregon counties.</i>*

County	Religious Organizations	Civic Associations	Labor Organizations	Votes Democrat	Vo
Baker	11	5	1	2195	
Benton	50	13	3	19444	
Clackamas	184	32	13	76421	
Clatsop	35	12	7	8296	
Columbia	29	5	3	10331	
Coos	40	9	7	11610	
Crook	14	3	0	2474	
Curry	13	1	1	4090	
Deschutes	62	29	8	22061	
Douglas	77	12	4	14193	
Gilliam	1	1	0	359	
Grant	4	1	0	589	
Harney	7	2	0	766	
Hood River	15	5	2	4072	
Jackson	90	26	14	33153	
Jefferson	11	1	0	2681	
Josephine	35	12	0	11864	
Klamath	45	15	6	7541	
Lake	6	2	0	707	
Lane	184	51	30	78583	
Lincoln	32	17	1	10861	
Linn	84	21	14	16682	
Malheur	22	3	0	2336	
Marion	156	30	25	49430	
Morrow	5	3	0	1197	

Table 4

*(#tab:descriptives tables)Table 4
 <i>A summary table for 2016: Selected social capital and voting behavior in Oregon counties.</i>*

County	Religious Organizations	Civic Associations	Labor Organizations	Democrat	Republic
Baker	20	8	1	1797	6218
Benton	66	13	5	29193	13445
Clackamas	215	20	18	102095	88392
Clatsop	31	11	3	9252	8138
Columbia	26	4	2	10167	13217
Coos	53	7	5	10448	17865
Crook	20	3	0	2637	8511
Curry	15	1	0	4300	7212
Deschutes	92	22	7	42444	45692
Douglas	90	7	3	14096	34582
Gilliam	2	1	0	239	671
Grant	8	1	0	739	3210
Harney	7	1	0	683	2912
Hood River	23	6	1	6510	3272
Jackson	112	19	13	44447	53870
Jefferson	15	1	0	2980	5483
Josephine	52	8	2	13453	26923
Klamath	46	8	3	7210	20435
Lake	6	3	0	639	3022
Lane	209	30	27	102753	67141
Lincoln	35	8	1	12501	10039
Linn	94	12	9	17995	33488
Malheur	22	2	2	2246	7194
Marion	191	19	21	57788	63377
Morrow	5	2	0	1017	2721
Multnomah	443	85	85	292561	67954