Supporting Information for "Partisan Conversion through Neighborhood Influence"

Contents

1 Voterfile Data and Panel Construction

Data for this study consists of yearly Target Smart snapshots from 2012-2020 for California, Florida, Kansas, New York, and North Carolina, and older state files (CA 2005, 2007, 2009; FL 2007, 2009; KS 2008; NY 2001, 2008; NC 2009). Target Smart identifies voters across time periods by linking individuals based on name, age, residential address, voting history, and other proprietary information. The vendor further identifies people changing addresses using records from the USPS National Change of Address database, and keeps track of deceased voters by comparing voter lists to the Social Security Death Master File.

I rely on Target Smart's linkages when comparing years from 2012 to 2020. To construct the longer panel, I link pre-2012 directly to the Target Smart files by first exact matching on first name, last name, birth year, and residential address. In order to account for potential surname changes, possibly due to marriage, I do a second link of the remaining unlinked sample by first name, birth year and residential address. As a last step, I match only on first name, last name, and residential address, to see if there are any potential links where age was differentially recorded.

Table S1 provides descriptive statistics of the linked (voters in the year 1 file who were located in the year 2 file at the same residence) and unlinked (all other voters in the year 1 file) samples for the linked voterfiles. The linked and unlinked samples are generally pretty similar, although there are differences in turnout, Block Group homeownership, Block Group median household income, and Block Group median house value, each of which are larger for the linked sample. Levels of partisan exposure and individual partisanship are similar.

2 Mover Analysis

Tables S2 reports the average levels of proportion Democrat and Republican in movers' new and old neighborhoods in the final years of their respective linked sample (2016 for 2012-2016, and 2020 for 2016-2020). The Census Block Groups that movers leave are only about 1 percentage points different in Democratic or Republican makeup from the Block Groups they move to.

Next, I model the decision to move as a function of changes in the Census Block Group[1] the

[1] I use Block Groups in this analysis, rather than individual measures of exposure as in the main analysis, since

Table S1: Mean Variable Levels Across Linked and Unlinked Samples

	2008-2012		2012-2016		2016-2020	
Variable	Linked	Unlinked	Linked	Unlinked	Linked	Unlinked
Age	51.202	48.013	53.375	47.791	51.892	46.532
Democrat	0.408	0.447	0.435	0.431	0.431	0.429
Republican	0.369	0.303	0.335	0.310	0.303	0.270
White	0.764	0.553	0.702	0.689	0.664	0.652
Black	0.082	0.114	0.093	0.100	0.104	0.116
Hispanic	0.091	0.119	0.122	0.124	0.151	0.153
Asian	0.033	0.032	0.042	0.037	0.047	0.041
Female	0.538	0.538	0.536	0.527	0.538	0.542
Vote General	0.826	0.685	0.600	0.503	0.067	0.033
Vote Primary	0.655	0.554	0.280	0.203	0.007	0.004
Block Group Democrat	0.400	0.450	0.425	0.430	0.428	0.433
Block Group Republican	0.361	0.310	0.321	0.313	0.294	0.283
Block Group White	65.246	57.147	0.593	0.585	0.565	0.550
Block Group Registered	0.615	0.618	0.517	0.502	0.621	0.624
Block Group Median Age	0.406	0.392	0.406	0.397	0.411	0.401
Block Group Median Household Income	69, 497	61, 573	69, 544	66, 175	70, 521	64, 696
Block Group Median Year House Built	1974	1970	1972	1973	1, 973	1, 974
Block Group Median House Value	343, 528	363, 856	339, 897	330, 520	356, 220	333, 232
Block Group Homeowner	75.213	60.531	0.687	0.633	0.649	0.587
Block Group Drive to Work	0.886	0.791	0.833	0.821	0.814	0.815
Democratic Exposure	0.402	0.453	0.423	0.428	0.429	0.434
Republican Exposure	0.357	0.302	0.309	0.295	0.285	0.267

Table shows the average levels of individual and aggregate variables across linked and unlinked samples for the 2008-2012, 2012-2016, and 2016-2020 linked samples.

Table S2: Partisan Differences in Old and New Neighborhoods for Movers

	2012-2016				2016-2020			
	% Democrat		% Republican		% Democrat		% Republican	
Party	Origin	New	Origin	New	Origin	New	Origin	New
Democrat	0.489	0.479	0.237	0.248	0.496	0.486	0.218	0.229
Non-Partisan	0.414	0.404	0.292	0.302	0.420	0.411	0.275	0.286
Republican	0.353	0.346	0.365	0.374	0.355	0.346	0.353	0.366

Table reports Block Group % Democrat and % Republican of origin and destination neighborhoods for movers.

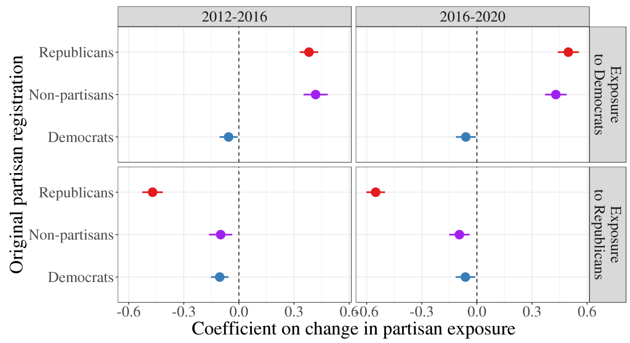


Figure S1: Effect of Census Block Group Changes in Partisan Exposure on Moving

voter lived in at the start of the panel. This test whether voters are more likely to move if the number of out-partisans in their neighborhood increases. I estimate models of the form:

$$\text{Move}_i = \ \alpha_{M_i} + \theta(\text{DE}_{i,2} - \text{DE}_{i,1}) + \tau HHDem_i + \lambda HHReg_i + \boldsymbol{\beta X}_i + \gamma_z + \epsilon_{i,c}$$

Figure S1 reports the results. Democrats' likelihood of moving slightly decreases in response to Democratic exposure, while Republicans or Non-Partisans become more likely to move. Democrats, Non-partisans, and Republicans become less likely to move in response to Republican exposure. This effect is largest for Republicans, but the decrease in Democratic mobility in response to Republican exposure is larger than the estimated effect of Democratic exposure on Democratic mobility. Thus, there is some evidence of differential mobility by partisanship in response to partisan exposure, but the results are inconsistent. Combined with the information that voters do not replace old neighborhoods with substantially more homogeneous ones, there does not appear to be clear evidence pointing towards partisan-motivated residential sorting.

3 Matched Strata Statistics

Here I present the summary statistics of the standard deviations of changes in Democratic and Republican exposure within strata. These strata are used in the main specification to narrow the scope of comparison in the estimation. For each linked sampled (2008-2012, 2012-2016, and 2016-2020) and for each subset (year 1 Democrats, Republicans, or Non-Partisans) within that sample, I calculate the within-strata standard deviation in Democratic and Republican Exposure. I also do

it is more straightforward to see what the Block Group exposure of a voter would have been if they had not left the Block Group.

Table S3: Average Within-Strata Standard Deviation of Changes in Partisan Exposure

		Main Specification			Pre-Trend Specification	
Exposure Type	Subset	2008-2012	2012-2016	2016-2020	2012-2016	2016-2020
Democratic	Democrats	0.067	0.057	0.059	0.056	0.054
Republican	Democrats	0.056	0.043	0.041	0.045	0.035
Democratic	Republicans	0.061	0.052	0.054	0.051	0.051
Republican	Republicans	0.069	0.059	0.061	0.052	0.041
Democratic	Non-Partisans	0.064	0.055	0.060	0.054	0.055
Republican	Non-Partisans	0.061	0.050	0.052	0.047	0.040

Table S4: Mean Levels of Variables by Party Switching

Years	Variable	Stable Democrat	Switch Democrat	Stable Republican	Switch Republican	Stable Non-Partisan	Switch Non-Partisan
2008-2012	Age	52	46	53	52	46	50
	Female	0.587	0.597	0.510	0.542	0.502	0.488
	White	0.655	0.618	0.882	0.832	0.769	0.772
	2008 Dem. Exp.	0.475	0.430	0.336	0.364	0.380	0.386
	2008 Rep. Exp.	0.296	0.321	0.428	0.404	0.348	0.371
	Δ Dem. Exp.	−0.007	0.013	−0.005	−0.016	−0.002	−0.008
	Δ Rep. Exp.	−0.020	−0.032	−0.027	−0.010	−0.025	−0.029
	Block Group White	0.589	0.564	0.714	0.689	0.669	0.655
	Block Group Med. HH Inc.	65,726	69,611	72,505	67,655	71,580	70,257
	Block Group Homeowner	0.724	0.726	0.782	0.770	0.755	0.754
2012-2016	Age	54	48	56	55	49	51
	Female	0.587	0.542	0.505	0.511	0.495	0.465
	White	0.578	0.597	0.857	0.823	0.708	0.721
	2012 Dem. Exp.	0.503	0.456	0.337	0.364	0.400	0.408
	2012 Rep. Exp.	0.243	0.271	0.395	0.370	0.304	0.319
	Δ Dem. Exp.	−0.004	0.015	−0.005	−0.015	−0.003	−0.008
	Δ Rep. Exp.	−0.014	−0.022	−0.014	0.001	−0.015	−0.018
	Block Group White	0.514	0.519	0.688	0.662	0.614	0.600
	Block Group Med. HH Inc.	65,014	68,677	72,504	67,789	70,731	69,196
	Block Group Homeowner	0.638	0.642	0.748	0.734	0.694	0.696
2016-2020	Age	52.000	48.000	56.000	53.000	47.000	49.000
	Female	0.592	0.567	0.505	0.498	0.498	0.499
	White	0.525	0.612	0.859	0.767	0.668	0.630
	2016 Dem. Exp.	0.516	0.443	0.327	0.368	0.404	0.427
	2016 Rep. Exp.	0.215	0.262	0.386	0.339	0.281	0.281
	Δ Dem. Exp.	0.001	0.021	0.001	−0.007	0.003	0.002
	Δ Rep. Exp.	−0.011	−0.022	−0.010	0.002	−0.011	−0.021
	Block Group White	0.478	0.526	0.680	0.613	0.582	0.522
	Block Group Med. HH Inc.	66,993	78,207	73,618	70,964	71,213	76,087
	Block Group Homeowner	0.590	0.637	0.727	0.700	0.656	0.655

this for the pre-trend specification strata. I report the average within-strata standard deviations in Table S3, showing that there is variation within strata in changes in partisan exposure, making the within Zip Code and other characteristic comparison feasible.

4 Descriptive Statistics and Main Results Tables

Table S4 presents average levels of descriptive variables for voters by partisan stability or partisan switching across the linked samples. Table S5 shows these statistics by levels of changes in Democratic and Republican exposure. Table S6 presents average levels and changes in household partisan composition across linked samples. Table S7 presents the full regression tables from the current effect main specifications.

Table S5: Mean Levels of Variables by Partisan Exposure

		Δ Dem. Exp.			Δ Rep. Exp.		
Sample	Variable	< -0.05	$[-0.05, 0.05]$	> 0.05	< -0.05	$[-0.05, -0.05]$	> 0.05
2008-2012	Age	50	52	49	50	51.000	50
	Female	0.543	0.537	0.545	0.541	0.540	0.540
	Democrat	0.436	0.397	0.408	0.363	0.441	0.380
	Republican	0.351	0.383	0.350	0.409	0.340	0.395
	White	0.774	0.771	0.723	0.768	0.742	0.830
	Block Group White	0.676	0.655	0.616	0.648	0.636	0.727
	Block Group Med. HH Inc.	63,749	71,935	69,314	72,936	68,451	65,709
	Block Group Homeowner	0.749	0.757	0.741	0.762	0.741	0.774
2012-2016	Age	53	54	52	53	54	53
	Female	0.541	0.535	0.541	0.538	0.537	0.534
	Democrat	0.452	0.426	0.450	0.383	0.460	0.363
	Republican	0.321	0.347	0.303	0.379	0.312	0.403
	White	0.714	0.708	0.662	0.722	0.679	0.812
	Block Group White	0.620	0.597	0.555	0.604	0.575	0.710
	Block Group Med. HH Inc.	60,607	70,958	69,243	70,349.000	68,769	65,698
	Block Group Homeowner	0.690	0.695	0.652	0.704	0.676	0.736
2016-2020	Age	51	52	51	52	52	52
	Female	0.546	0.539	0.540	0.539	0.542	0.538
	Democrat	0.459	0.423	0.432	0.368	0.465	0.342
	Republican	0.276	0.318	0.283	0.357	0.275	0.381
	White	0.618	0.670	0.678	0.723	0.625	0.776
	Block Group White	0.540	0.567	0.577	0.607	0.532	0.678
	Block Group Med. HH Inc.	59,122	71,172	78,543	81,030	68,586	62,931
	Block Group Homeowner	0.635	0.657	0.640	0.694	0.627	0.703

Table S6: Mean Levels and Changes in Household Partisan Composition

		Year 1 Household			Avg. Change Household		
Party (Year 1)	Years	Registrants	Democrats	Republicans	Registrants	Democrats	Republicans
Democrat	2008-2012	0.903	0.617	0.139	-0.017	-0.026	-0.001
Republican	2008-2012	1.026	0.152	0.716	-0.019	-0.002	-0.035
Non-partisan	2008-2012	0.920	0.249	0.241	-0.001	0.010	-0.002
Republican	2012-2016	0.955	0.140	0.651	0.013	0.003	-0.005
Non-partisan	2012-2016	0.816	0.236	0.194	0.025	0.014	0.006
Democrat	2012-2016	0.806	0.558	0.106	0.010	-0.002	0.003
Republican	2016-2020	0.964	0.133	0.653	0.024	0.012	-0.007
Non-partisan	2016-2020	0.788	0.231	0.186	0.051	0.034	0.012
Democrat	2016-2020	0.765	0.527	0.091	0.023	0.007	0.004

Table shows the average number of same-household registrants, Democrats, and Republicans – and the average change in these quantities, for the 2008-2012, 2012-2016, and 2016-2020 linked samples, reported separately by starting partisanship.

Table S7: Current Effects Main Specification Regression Tables

DV: Δ Dem. Reg.	2008-2012			2012-2016			2016-2020		
	'08 Reps	'08 NPs	'08 Dems	'12 Reps	'12 NPs	'12 Dems	'16 Reps	'16 NPs	'16 Dems
Δ Dem Exp	0.040	0.075	0.062	0.033	0.085	0.056	0.073	0.176	0.094
	(0.004)	(0.008)	(0.005)	(0.003)	(0.009)	(0.004)	(0.006)	(0.011)	(0.005)
Δ HH Democrats	0.064	0.066	0.103	0.059	0.065	0.093	0.115	0.124	0.098
	(0.004)	(0.005)	(0.009)	(0.005)	(0.009)	(0.014)	(0.006)	(0.012)	(0.011)
Δ HH Voters	-0.007	-0.014	-0.070	-0.006	-0.012	-0.063	-0.012	-0.023	-0.070
	(0.001)	(0.001)	(0.006)	(0.000)	(0.002)	(0.009)	(0.001)	(0.003)	(0.006)
Δ BG White	-0.001	0.003	0.000	-0.001	-0.001	0.000	0.000	0.003	-0.001
	(0.001)	(0.004)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)
Δ BG Age	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ BG Reg.	0.000	-0.002	-0.001	0.000	0.000	0.000	-0.001	0.002	-0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Δ BG HH Income	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ BG Homeowner	-0.001	-0.002	0.000	0.000	0.002	0.000	0.000	0.001	0.000
	(0.001)	(0.003)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Δ BG Med. Year Built	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ BG Drive Work	0.000	-0.004	-0.004	0.001	0.000	0.000	-0.002	-0.001	0.000
	(0.002)	(0.004)	(0.002)	(0.001)	(0.003)	(0.001)	(0.002)	(0.004)	(0.001)
Δ BG Med. Home Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ Married				0.000	0.005	-0.010	-0.005	-0.006	0.000
				(0.000)	(0.001)	(0.001)	(0.001)	(0.004)	(0.002)
Δ BG College				0.000	0.003	0.000	-0.001	-0.001	-0.001
				(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)
Δ BG Unemployed				-0.001	-0.001	0.000	0.002	0.005	0.001
				(0.001)	(0.003)	(0.002)	(0.002)	(0.004)	(0.002)
Num.Obs.	6,052,389	3,648,978	6,684,288	6,960,759	4,713,332	8,681,329	8205468	6,913,541	10,743,631
R^2	0.505	0.572	0.454	0.537	0.568	0.479	0.493	0.511	0.444
R^2 Adj.	0.221	0.137	0.104	0.200	0.092	0.113	0.176	0.098	0.106

DV: Δ Rep. Reg.	2008-2012			2012-2016			2016-2020		
	'08 Reps	'08 NPs	'08 Dems	'12 Reps	'12 NPs	'12 Dems	'16 Reps	'16 NPs	'16 Dems
Δ Rep. Exp	0.046	0.070	0.066	0.034	0.085	0.068	0.070	0.113	0.100
	(0.005)	(0.008)	(0.005)	(0.003)	(0.010)	(0.004)	(0.007)	(0.010)	(0.005)
Δ HH Republicans	0.065	0.120	0.151	0.057	0.147	0.166	0.099	0.140	0.173
	(0.003)	(0.013)	(0.011)	(0.004)	(0.017)	(0.015)	(0.005)	(0.008)	(0.012)
Δ HH Voters	-0.042	-0.020	-0.015	-0.036	-0.022	-0.014	-0.065	-0.016	-0.012
	(0.002)	(0.003)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)	(0.002)
Δ BG White	-0.001	0.000	-0.001	-0.001	0.003	0.000	-0.001	-0.002	0.001
	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Δ BG Age	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ BG Reg.	0.002	0.000	0.001	0.000	0.000	-0.001	0.000	0.001	0.000
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Δ BG Med. HH Income	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ BG Homeowner	0.001	0.003	0.000	-0.002	0.000	-0.001	0.001	0.000	0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Δ BG Med. Year Built	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ BG Drive Work	0.001	0.000	0.001	0.000	0.000	0.000	0.002	0.000	0.001
	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Δ BG Home Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ Married				-0.005	0.009	0.004	0.005	-0.001	-0.002
				(0.001)	(0.001)	(0.000)	(0.003)	(0.002)	(0.001)
Δ BG College				0.002	-0.002	0.001	0.002	0.003	0.000
				(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Δ BG Unemployed				0.002	-0.002	-0.001	-0.004	-0.003	-0.002
				(0.003)	(0.003)	(0.001)	(0.003)	(0.003)	(0.002)
Num.Obs.	6,052,389	3,648,978	6,684,288	6,960,759	4,713,332	8,681,329	8205468	6913541	10,743,631
R^2	0.478	0.565	0.463	0.517	0.579	0.483	0.490	0.512	0.457
R^2 Adj.	0.139	0.130	0.156	0.119	0.127	0.163	0.126	0.112	0.171

5 Simulation Analysis of Within-Zip Code Switching

To assess the sensitivity of the estimation to spatially clustered party switching that is not accounted for by matching voters on Zip Code, I conduct a simulation that generates increasingly stronger within-Zip Code party switching. The aim is to assess how much of this clustered switching it would take for the estimation of the current effects to return coefficients as large as the effects obtained in the main analysis.

The simulation was run on the sub-sample of voters in California in the 2012-2016 linked sample, and focused on how generating spatially clustered Democratic party switching would influence the estimation of the effect of Democratic exposure on Democratic partisanship. Within-Zip Code party switching was generated by measuring the distance in meters that each voter lives from the centroid of their Zip Code. Voters were then binned into within-Zip Code distance decile groups, creating a variable for each voter that ranges from 1 to 10, with 10 representing the 10% of voters that live closest to the center of the Zip Code. Using this variable, each voter was assigned a probability of being a Democrat in 2016. For voters that were not Democrats in 2012, this was based on the following formula, with proximity to the Zip Code centroid increasing the likelihood of becoming a Democrat:

$$P(D_{t+1} = 1|D_t = 0) = \sigma^{-1}(\mu_i + \beta Dist_i)$$

where μ_i is an individual intercept parameter drawn from a normal distribution $N(-10, 1)$, and β is the parameter controlling the relationship between proximity to the Zip Code centroid and Democratic partisanship. β values consist of 0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.55, 0.6, 0.65, 0.7, 0.75, 0.80, 0.85, 0.90, 0.95, and 1. $\sigma^{-1}(\cdot)$ is the inverse logit function mapping the linear model $\mu_i + \beta Dist_i$ to probability values between 0 and 1.

For voters that were already Democrats, party switching was generated such that proximity to the Zip Code increased the likelihood of remaining a Democrat. For these voters, the $Dist_i$ variable was reversed coded (so that 10 is now furthest away from the Zip Code centroid), and the probability was derived from the following formula:

$$P(D_{t+1} = 1|D_t = 1) = 1 - \sigma^{-1}(\mu_i + \beta RevDist_i)$$

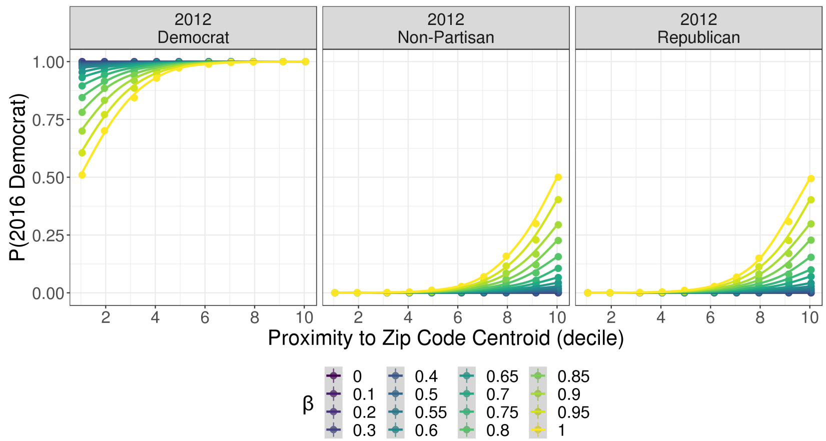


Figure S2: 2016 Democrat probability across simulation β

Figure plots the average simulated probability of being a Democrat in 2016 as a function of distance to voters' Zip Code centroids. Points are plotted separately by values of β.

Figure S2 plots the likelihood of being a Democrat as a function of distance to the Zip Code centroid across voters in the linked sample, plotted separately by starting partisanship, and with separate plots for each β parameter. With these probabilities, partisan changes were simulated by drawing from a Bernoulli distribution (Democrat or Not Democrat) for each voter. This setup makes it such that the only party switching occurring in the data is a function of proximity to the Zip Code centroid. Ten simulated datasets were generated. For each simulated dataset, partisan exposure was re-calculated by identifying the 1,000 nearest neighbors for each voter and using the simulated Democratic partisanship to calculated the weighted proportion of Democrats. These new partisan exposure measures were then used to construct the treatment variable, the change in Democratic exposure from 2012 to 2016. The simulated data was also used to update the outcome, at which point the specification from the main analysis was estimated.

Figure S3 plots the average point estimate across simulated datasets for increasing values of β. For interpretability, the X-axis is translated to the ratio of changes in Democratic registration generated by the within-Zip code parameter compared to the levels observed in the real data. This allows for direct evaluation of how much within-Zip Code partisan switching would have to be generated in this setup for to observe estimates at similar sizes as the main analysis. As the figure shows, the estimates do increase as the intensity of within-Zip Code switching increases, but in order for within-Zip Code switching to completely explain the effect it would have to generate

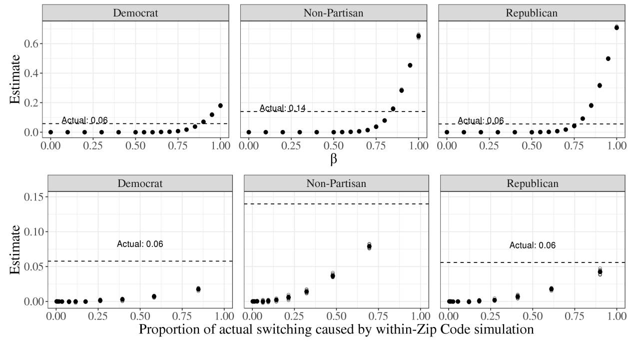


Figure S3: Estimated effect by intensity of within-Zip Code party switching

Figure plots the estimates of the effect of Democratic exposure on Democratic partisanship for the 2012-2016 linked California sample. The x-axis in the top row figure is the β parameter from the simulation. The x-axis in the bottom row is the ratio of simulated changes in Democratic partisanship to actual changes in Democratic partisanship. Horizontal dashed lines represent the actual results from the current results main specification from the 2012-2016 linked California sample. Top panel shows simulation results across all values of β, while bottom panel is limited to comparable proportions of party switching between 0 and 1.

levels of partisan switching as high as 100% or higher of the rate observed in the data, depending on starting partisanship. Within-Zip Code shocks accounting for 100% of all party switching is implausible, and proportions close to 100% are similarly unlikely, given the individual factors and larger contextual influences on partisanship.

6 Simulation Analysis of Census Block Shocks

I also conduct a second simulation to further test the sensitivity of the estimates to local shocks to partisanship. In this simulation, I generate common Census Block-level shocks to Democratic partisanship. Similar to the previous simulation, this analysis was run on voters in California in the 2012-2016 linked sample, and measures how shocks to Democratic partisanship influence the measured effect of Democratic exposure.

In each run of the simulation, block-level shocks were generated by randomly drawing from a normal distribution $\epsilon_b \sim N(0, \sigma^2)$. I also drew an individual random effect for each voter from the standard normal distribution ($\epsilon_i \sim N(0,1)$). An intercept α was also calculated based on average levels of 2016 Democratic partisanship within each 2012 partisanship subset.[2] Democratic partisanship in 2016 was then generated based on an indicator variable, $\mathbf{1}(\alpha + \epsilon_i + \epsilon_b \geq 0)$.

[2] In order to ensure that the total amount of simulated switching in each draw was similar to the total amount of switching in the data, α was adjusted down at higher values of σ^2, since otherwise the uneven distribution of voters across Census Blocks would cause higher values of σ^2 to result in too high levels of party switching.

Ten runs of the simulation were run for values of σ^2: 0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0. After simulating 2016 Democratic partisanship, I re-calculate the neighbor and household partisan exposure measures and re-estimate the main specifications using these simulated exposure and simulated outcome.

Figure S4 presents the average estimates from the simulation run. In order to benchmark plausible levels of Census Block-level shocks to party switching, I estimate the variance of average party switching across Blocks, and compare that to the average within-Block variance, from the formula $V[Y] = E[V[Y|B]] + V[E[Y|B]]$, where $Y = D_{t+1} - D_t$ and B is the Census Block. Common shocks to voters in the same Census Block correspond to the $V[E[Y|B]]$. Thus, the ratio of $\frac{V[E[Y|B]]}{E[V[Y|B]]+V[E[Y|B]]}$ represents a useful benchmark for comparing the likely variance of ϵ_b in relation to the variance of ϵ_i and the total variance of party switching ($\sigma_y^2 = \sigma_{\epsilon_i}^2 + \sigma_{\epsilon_b}^2$) – i.e. what proportion of the variance in party switching could plausibly be explained by Block-level shocks.[3] In the data, $\frac{V[E[Y|B]]}{E[V[Y|B]]+V[E[Y|B]]} \approx 0.162$. This ratio applied to the simulation ($\frac{\sigma_{\epsilon_b}^2}{\sigma_{\epsilon_i}^2+\sigma_{\epsilon_b}^2}$) corresponds to a σ^2 value of 0.193.

Figure S4 plots a horizontal dotted line at this benchmark. At this benchmark, Block-level shocks generate effect estimates much smaller than the observed effects. For Block-level shocks to generate estimates as large as those from the main effects the variance would have to be as large as 0.4 to 0.7, depending on starting partisanship subset, meaning the Block-level shocks would have to explain from 28%-41% or more of the variance in party-switching, significantly larger than the likely benchmark from the block-level variation in the data.

7 Additional Panel Results

7.1 Results by District Electoral Competitiveness

If campaign activity is driving the effects then results should be larger in competitive electoral districts, and potentially non-existent in uncompetitive ones. To test this, I subset the 2012-2016 and 2016-2020 linked samples by House district, and re-estimate the main specification within these

[3] This benchmarking assumes that the Block-level shock is unrelated to the treatment effect from neighbor partisan exposure. But neighbor influence could itself increase the variance across Blocks, so it is possible that the true benchmark is lower.

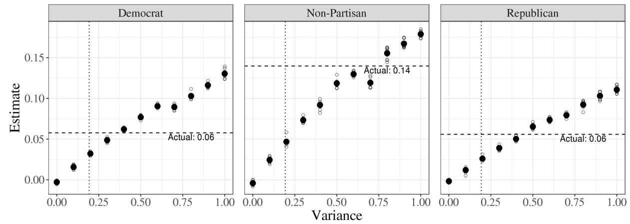


Figure S4: Estimate effect by variance of Census Block-level shock

Figure plots the estimates of the effect of Democratic Exposure on Democratic partisanship for the 2012-2016 linked California sample. The x-axis is the variance of the Block-level shock. Horizontal dashed lines represent the actual results from the. current results main specification from the 2012-2016 linked California sample. The vertical dotted line represents the benchmark of Block-level shock variance.

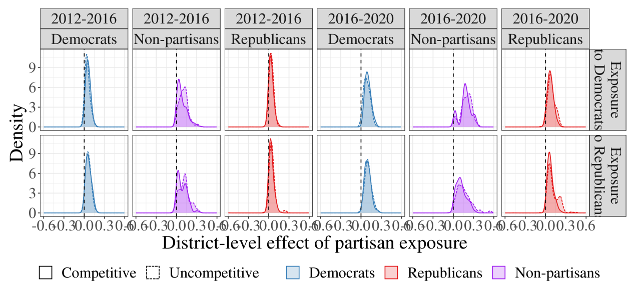


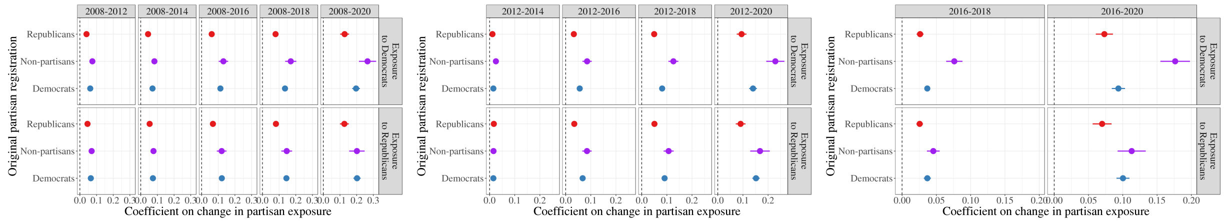
Figure S5: District Electoral Competition is not Determinant of Effect Size

Figure plots the distribution of current effects across U.S. House districts for the 2012-2016 and 2016-2020 linked samples. Distributions are weighted by voters in the sample in each district. Distributions are plotted separately for year 1 Democrats (blue), Republicans (red) and Non-Partisans (purple) for each linked sample. Effects of Democratic exposure on Democratic partisanship are in the top row, and effects of Republican exposure on Republican partisanship are in the bottom row. Overlaid histograms plot effects for competitive (solid lines) and uncompetitive (dashed lines).

district subsets. I then classify each district as competitive if across the time period the same party represented the district, and the minimum margin of victory never fell below 20 percentage points. Figure S5 shows the distribution of these district-level estimates across districts, weighting by sample size in each district, plotting separate histograms for competitive and uncompetitive districts. Not only do the results persist in uncompetitive districts but the distributions for competitive and uncompetitive districts almost entirely overlap, indicating that electoral competition is not determinant of effect size.

7.2 Main Results Across Other Time Periods and by State

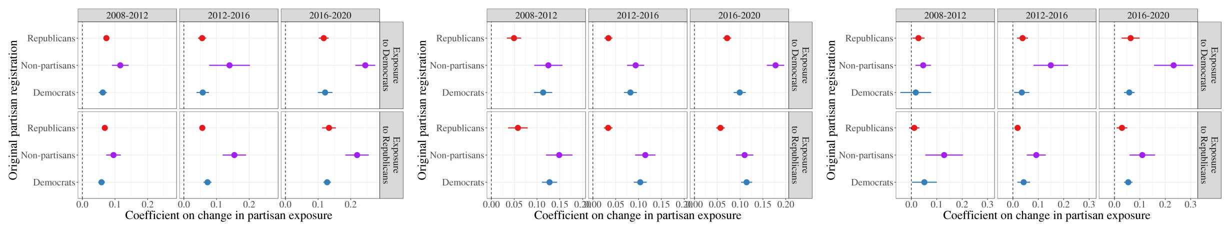
Here I present current results across alternative time periods. I created linked samples connecting 2008 to 2012, 2014, 2016, 2018 and 2020, linking 2012 to 2014, 2016, 2018 and 2020, and connecting 2016, to 2017, 2018, 2019 and 2020. I estimated the main specification effects for all of these years.



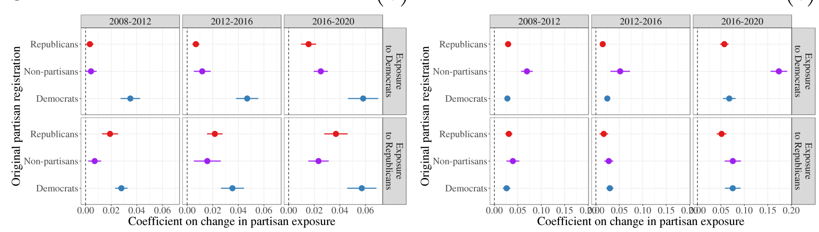
(a) 2008 samples (b) 2012 samples (c) 2016 samples

Figure S6: Effect of Partisan Exposure Across Multiple Time Periods

Figure plots the effect of Democratic and Republican exposure across alternative linked samples. Results are plotted separately based on partisanship in the first year of each linked sample.



(a) CA (b) FL (c) KS



(d) NC (e) NY

Figure S7: Effect of Partisan Exposure by State

Figure plots the current effect of Democratic and Republican exposure by state. Results are plotted separately based on partisanship in the first year of each linked sample.

Next, I present the main current results broken out by state. The patterns observed in the pooled samples are consistent across states, with all states exhibiting consistent direction of the effects.

7.3 Alternative Estimation

Next, I present the results under alternative definitions of treatment and alternative specifications. Excepted where noted otherwise, each alternative estimation below described below is identical to the main current results specification in the manuscript. I present these results for the 2012-2016 and 2016-2020 linked samples. These include:

1. Aspatial exposure, the proportion of Democrats or Republicans in each voter's 1,000 nearest

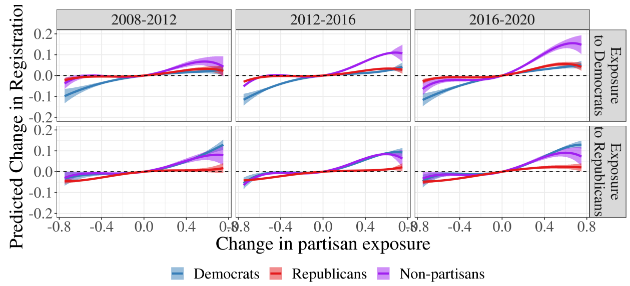


Figure S8: Marginal Effect of Partisan Exposure is Increasing with Size of the Change in Partisan Exposure

Figure plots the predicted change in Democratic (top row) or Republican (bottom row) partisanship in the final year of each (2008-2012, 2012-2016, 2016-2020) linked sample as a function of the size of the shift in partisan exposure. Predictions come from the main specification model with second, third, and fourth order polynomial terms of the treatment added in.

neighbors, with no distance weighting.

2. Spatial Democratic ratio of Republicans and Democrats, the spatially weighted proportion of Democrats out of the all the Democrats and Republicans in a voter's 1,000 nearest neighbors (dropping non-partisans from the denominator).
3. Spatial exposure including neighbors living in the same household as the voter.
4. Spatial exposure within each voter's 100 and 500 nearest neighbors.
5. Spatial exposure within 1 mile of each voter.
6. Change in number of new Democratic or Republican neighbors (not counting neighbors who switch).
7. Census Block and Census Block Group proportions of Democrats and Republicans out of total registered voters in the Census geography.
8. Main specification but using posterior probability of being White as the race variable rather than categorical imputations.[4]

7.4 Polynomial Specification

To test for non-linearity in the effects, I estimate an alternative specification adding in second, third, and fourth-order polynomial transformations of changes in Democratic and Republican partisan exposure. With the estimates from these models, in Figure S8 I plot the predicted change in likelihood of registering Democrat or Republican across different levels of changes in Democratic or Republican exposure.

[4]Target Smart provides posteriors only for the 2020 data, so these results are only estimated for the 2016-2020 linked sample.

Table S8: Alternative Treatment Estimates

	Current Results: 2012-2016					
	DV: Democratic Registration			DV: Republican Registration		
Treatment	Democrats	Republicans	Non-Partisans	Democrats	Republicans	Non-Partisans
Main	0.056	0.033	0.085	0.068	0.034	0.085
	(0.004)	(0.003)	(0.009)	(0.004)	(0.003)	(0.01)
Pre-trend	0.127	0.127	0.119	0.143	0.044	0.138
	(0.01)	(0.01)	(0.013)	(0.009)	(0.005)	(0.009)
Aspatial	0.021	0.017	0.021	0.019	0.009	0.027
	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.01)
Dem. Ratio	0.063	0.025	0.053	-0.053	-0.035	-0.061
	(0.004)	(0.003)	(0.005)	(0.003)	(0.004)	(0.007)
Include Same Household	0.165	0.043	0.106	0.158	0.063	0.128
	(0.013)	(0.004)	(0.01)	(0.009)	(0.003)	(0.013)
100 Neighbors	0.034	0.02	0.054	0.043	0.022	0.054
	(0.003)	(0.002)	(0.006)	(0.003)	(0.002)	(0.007)
500 Neighbors	0.049	0.029	0.075	0.059	0.029	0.074
	(0.004)	(0.003)	(0.008)	(0.003)	(0.003)	(0.008)
Mile Radius	0.054	0.029	0.08	0.062	0.03	0.078
	(0.004)	(0.003)	(0.009)	(0.004)	(0.003)	(0.009)
New Neighbors	0.003	0.012	0.04	0.015	0.007	0.029
	(0.004)	(0.006)	(0.012)	(0.006)	(0.006)	(0.009)
Census Block	0.003	0.004	0.011	0.005	-0.004	0.003
	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)	(0.003)
Census Block Group	0.005	0.011	0.041	0.007	-0.012	0.005
	(0.006)	(0.007)	(0.016)	(0.005)	(0.007)	(0.009)

	Current Results: 2016-2020					
	DV: Democratic Registration			DV: Republican Registration		
Treatment	Democrats	Republicans	Non-Partisans	Democrats	Republicans	Non-Partisans
Main	0.094	0.073	0.176	0.1	0.07	0.113
	(0.005)	(0.006)	(0.011)	(0.005)	(0.007)	(0.01)
Pre-trend	0.143	0.143	0.246	0.171	0.098	0.165
	(0.01)	(0.01)	(0.015)	(0.006)	(0.011)	(0.016)
Aspatial	0.05	0.035	0.05	0.04	0.035	0.037
	(0.007)	(0.006)	(0.007)	(0.005)	(0.007)	(0.008)
Dem. Ratio	0.102	0.054	0.112	-0.079	-0.076	-0.087
	(0.005)	(0.005)	(0.008)	(0.004)	(0.007)	(0.009)
Same Households	0.187	0.098	0.218	0.182	0.072	0.121
	(0.01)	(0.008)	(0.013)	(0.009)	(0.006)	(0.009)
100 Neighbors	0.059	0.045	0.113	0.064	0.047	0.077
	(0.003)	(0.004)	(0.006)	(0.003)	(0.005)	(0.007)
500 Neighbors	0.081	0.063	0.155	0.088	0.062	0.101
	(0.004)	(0.005)	(0.009)	(0.004)	(0.006)	(0.01)
Mile Radius	0.09	0.065	0.167	0.093	0.061	0.102
	(0.005)	(0.006)	(0.011)	(0.005)	(0.007)	(0.01)
New Neighbors	0.005	0.01	0.028	-0.002	0.009	0.024
	(0.004)	(0.005)	(0.014)	(0.006)	(0.006)	(0.011)
Census Block	0.018	0.007	0.024	0.018	0.002	0.009
	(0.003)	(0.002)	(0.005)	(0.002)	(0.002)	(0.003)
Census Block Group	0.027	0.026	0.063	0.033	0.022	0.01
	(0.01)	(0.009)	(0.017)	(0.006)	(0.009)	(0.011)
Race Posteriors	0.101	0.083	0.183	0.106	0.081	0.122
	(0.005)	(0.008)	(0.012)	(0.005)	(0.01)	(0.013)

7.5 Household Exposure Placebo Results

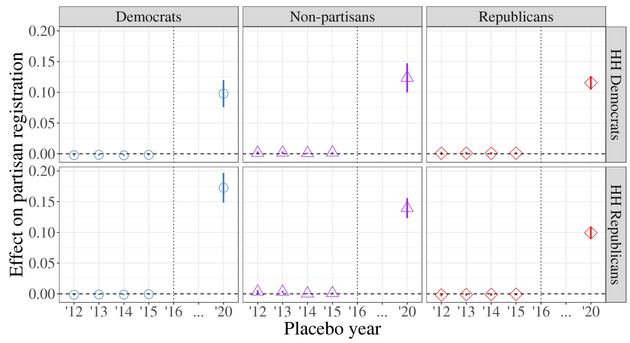


Figure S9: HH Placebo Trends

8 Heterogeneous results: age, housing type, and neighbor race

8.1 Theoretical motivation

Registration effects should be strongest for voters most likely to be connected to their community, interact with neighbors, and be influenced by the people they live near. I examine several such sources of heterogeneity: voter age, housing, and racial similarity with neighbors. Survey data demonstrate that community trust and interactions with neighbors are increasing with age, possibly due to higher levels of homeownership, longer tenure, less cross-pressure from competing social networks, or different patterns of social interaction (Parker et al., 2018). Consequently, while older voters may exhibit stabler partisan affiliations overall (Hobbs, 2019), they may be more influenced to adopt neighbors' partisanship.

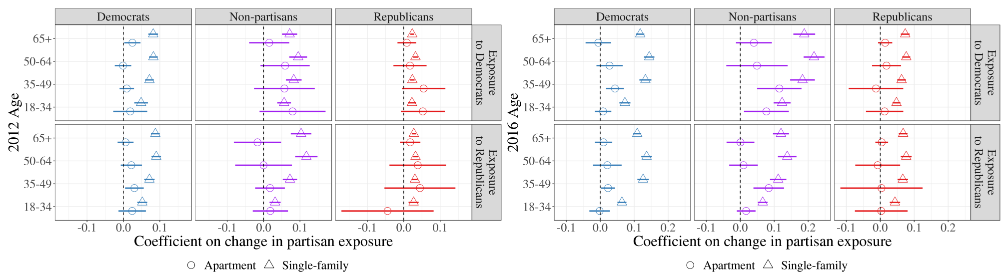
The built environment may also structure how voters interact with and are influenced by those they live around. Hopkins and Williamson (2010), for example, demonstrate the influence of design features on political participation in rural, suburban, and urban communities. I focus on the different effects of local influence for voters living in single-family housing versus those living in high-rise apartments. Voters living in single-family communities may more readily observe their neighbors and interact with them compared to voters living in high-rises, since it is easier to see the neighbor across the street, and walk over to talk to them, than the neighbor living several floors up in the same building. Living in high-density cities where neighbors are vertically integrated has been shown to reduce local ties (Fischer, 1982), and urban residents report lower levels of trust in their neighbors than rural or suburban residents (Parker et al., 2018). Some of these differences may be a function of other demographics (i.e. homeownership, age, income) that, in combination with the direct influence of housing, strengthen the hypothesis that voters will be more influenced by their neighbors in single-family communities than in high-rise housing.

Lastly, voters may be most influenced by neighbors who are similar to them along other characteristics, particularly race. Voters rely on racial categorization and identification when choosing their political party (Mangum, 2013), and local context can strengthen both racial identity and its influence on political attitudes (Gay, 2004). Other research argues that race is the most powerful determinant of divisions in local politics (Hajnal and Trounstine, 2014), and a primary source of growing partisan polarization at the national level (Abramowitz and McCoy, 2019). Racial homogeneity is a powerful predictor of community cohesiveness and group political attitudes (Hutchings and Valentino, 2004; Putnam, 2007), and voters may be more likely to interact with same race neighbors, or may perceive a sense of shared identity that makes them more responsive to partisan cues.Therefore, a voter that sees increasing partisan exposure may be most influenced by these changes if the change comes from same-race neighbors. Exposure to racial out-groups may also produce backlash effects that supplant the influence of partisan exposure. For example, exposure to Hispanics has been shown to increase White Republican partisanship (Hajnal and Rivera, 2014).

8.2 Heterogeneous Results

Here, I present results by 1) voter age 2) whether voters live in single-family homes or apartments, and 3) whether increased partisan exposure comes from same-race neighbors.

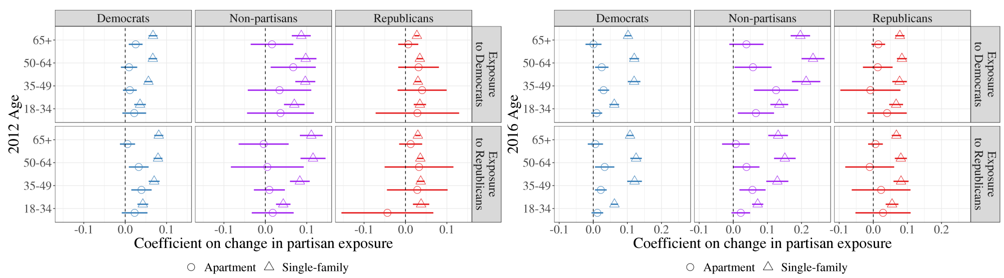
I subset the data by age and housing type and estimate the main current effect specifications for the 2012-2016 and 2016-2020 linked samples within subsets. Figure S10 presents the results for the 2016-2020 sample by age and housing type subsets, plotting for each age group (18-34, 35-49, 50-64, and 65 and over) the effect for voters living in single-family homes and those living in apartments. The results are larger for voters living in single-family homes, while the effects for voters in apartments are muted. The effects are generally increasing by age within the single-family home group, but do not vary substantially by age for voters in apartments.



(a) 2012-2016

(b) 2016-2020

Figure S11: Effect of Partisan Exposure by Age and Housing Type – White Voters



(a) 2012-2016

(b) 2016-2020

Figure S10: Effect of Partisan Exposure by Age and Housing Type

Figure plots effect of a one unit (100 percentage point) increase in Democratic exposure on Democratic partisanship (top row) and effect of a similar increase in Republican exposure on Republican partisanship (bottom row) for the 2012-2016 and 2016-2020 linked sample, from the current effect specifications. Results are plotted separately by subsets of age (Y-axis) and whether the voter lives in a single-family home (triangles) or an apartment (circles). Results are plotted separately for subsets based on partisanship in the first year of the linked sample. Bars plot 95% confidence intervals.

Next I show the same results for the 2012-2016 linked sample, as well as the 2012-2016 and 2016-2020 results subset to just White voters. Housing type is not measured in the earlier state voterfiles, so I do not estimate 2008-2012 results. Subsetting to Whites shows that the patterns observed in the age and housing subsets are not a result of unequal distributions of race across these subsets.

To test whether voters are most influenced by neighbors of the same race as them, I estimate four separate interaction models. The first operationalizes partisan exposure as exposure to White Democrats or White Republicans out of each voter's 1,000 nearest neighbors and interacts an indicator variable for whether a voter is White with change in partisan exposure, and all other covariates in the model. If same-race neighbors are most influential, then effect for ingroup voters should be larger for outgroup voters. The other three specifications are similar in structure, but with partisan exposure operationalized by exposure to Black, Asian, and Hispanic neighbors, respectively, with the corresponding interaction term for that race.[5]

Figure S12 plots the effects from these models. Exposure to White partisans generally has the largest effects for White voters, compared to non-White voters. The results for Asians (and exposure to Asian partisans) and Hispanics (and exposure to Hispanic partisans) mirror those for Whites, but the effect of Black partisan exposure for Blacks is generally statistically indistinguishable from that for Non-Blacks.

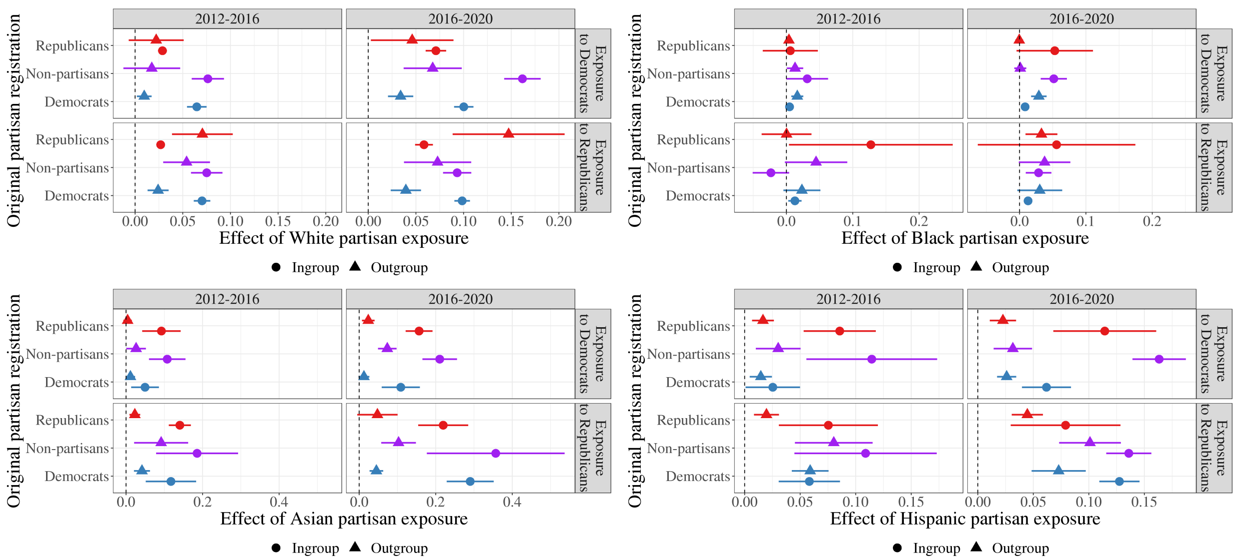


Figure S12: Voters are Most Influenced by Same-Race Neighbors

Top left figure plots effect of exposure to White Democrats or White Republicans, from the current effect specifications. Points are plotted separately for in-group and out-group voters. The other figures plot the same coefficients, but from models interacting whether a voter is Asian, Black, or Hispanic (bottom left, top right, bottom right) and partisan exposure from neighbors of that race. Bars plot 95% confidence intervals.

9 Survey

The survey was in the field from June 29, 2020 to August 28, 2020, administered from email lists linked to voter data. The survey was taken online through Qualtrics. Surveys were delivered by

[5]These models are of the form:

$$D_{i,2} - D_{i,1} = \alpha_M + \theta(ZDE_{i,2} - ZDE_{i,1}) + \boldsymbol{\beta}(\boldsymbol{X}_{i,2} - \boldsymbol{X}_{i,1}) + \tau Z_i * (ZDE_{i,2} - ZDE_{i,1}) + \boldsymbol{\eta} Z_i * (\boldsymbol{X}_{i,2} - \boldsymbol{X}_{i,1}) + \epsilon_i$$

where $ZDE_{i,t}$ is the spatially weighted proportion of Democratic neighbors who are race z among voter i's 1,000 nearest neighbors, and Z_i is an indicator variable for if voter i is race z.

e-mail via Qualtrics, and e-mails were drawn from e-mail lists connected to voterfile data by Target Smart. The survey was nationwide, with voters randomly drawn from the email list, and a large oversample was taken in the 5 states from the panel analysis. Sampled voters were sent an initial e-mail inviting them to be in the survey, and follow-up reminder emails were sent each week for the following 3 weeks. In total, 4,826,036 voters were contacted, with 76,576 total responses for a response rate of 1.59%. Of these responses, 92.3% verified that they were the person listed on the voterfile. For the analysis in this paper I limit the sample to voters who were also in the panel analysis (and thus living in California, Florida, Kansas, New York, or North Carolina), and who verified their identity, leaving a sample of 24,623 voters.

Participation in the survey was voluntary. Participants were not compensated for participation in the survey and were aware they were taking part in a research study. Compensation was not offered due to budgetary constraints and participants were informed at the start that there would be no compensation for participation in the study. Informed consent was obtained from subjects prior to starting the survey. Potential respondents who chose to follow the survey link in the invitation email were first taken to the informed consent form. The informed consent included explanations of the general purpose of the research, to collect voters' opinions about politics and current events. The informed consent also included an explanation that their responses could be linked to public voter records by the researchers. Voters were not allowed to start the survey until they had confirmed their consent to take part in the research. No deception was used in the survey. The study intervened in no political processes.

In the analysis, I use survey weights designed to make the survey sample look more like the registered population of the states in the sample. Survey weights were constructed by estimating a logistic regression, fit to all the voters in the five states, modeling being in the sample as a function of voter age, gender, race, party, state, 2016 turnout, and 2018 turnout:

$$\text{Survey}_i = \alpha + \text{Age}_i + \text{Race}_i + \text{Party}_i + \text{State}_i + \text{Vote 2016}_i + \text{Vote 2018}_i + \text{Gender}_i + \epsilon_i$$

From this model I calculate the probability of being in the sample and invert the probability (1/p) to get the survey weight for each voter. Table S9 shows the mean levels of variables for the survey sample compared to the registered voting population of the 5 states from the panel. The table also

Table S9: Survey Descriptive Statistics and Population Comparisons

Status	Registered Population	Sample	Sample Weighted
Democrat	0.424	0.412	0.379
Married	0.370	0.537	0.417
Republican	0.271	0.366	0.280
White	0.641	0.856	0.631
Black	0.103	0.051	0.095
Hispanic	0.165	0.052	0.177
Asian	0.050	0.018	0.055
Female	0.511	0.513	0.509
Age	50.097	62.097	54.131
Democratic Exposure	0.433	0.380	0.420
Republican Exposure	0.264	0.317	0.276
Block Group White	0.543	0.670	0.566
Block Group Registered	0.481	0.626	0.588
Block Group Median Age	41.294	43.759	41.271
Block Group Median Household Income	78,957	84,541	80,408
Block Group Homeowner	0.629	0.712	0.657
Block Group Median Year House Built	1974	1978	1973
Block Group Drive to Work	0.810	0.847	0.828
Block Group Median House Value	421,767	404,466	404,969
Vote 2016 General	0.662	0.951	0.618
Vote 2018 General	0.576	0.912	0.520

shows the average levels of the variables when accounting for survey weights, which generally move the average levels of variables for the survey sample towards the averages of the broader population.

10 Impact of Social Influence on Segregation

Here, I present the results from a simulation designed to measure the change in geographic polarization caused by the social influence effects identified in the main analysis. To do so, I take the 2012-2020 linked samples (voters who did not change residences between 2012 and 2020), estimate the main specifications from the analysis (modeling changes in partisanship from 2012-2020 as a function of changes in partisan exposure from 2012-2020), and then simulate party switching across this time period from those models, except with the coefficients on Democratic and Republican exposure set to 0. This simulation thus emulates what party switching would have looked like if local partisan exposure were having no effect on party switching. With the simulated datasets, I calculate common metrics of partisan segregation: the county-level dissimilarity index, and the county-level relative share of the electorate that is Democrat versus Republican. I then compare the results of the simulation to the actual changes observed in the data to see how these metrics would change if social influence were not a factor.

Table S10: Full survey results – Perception of neighbors' party, contact with partisan neighbors, and comfort with neighbors' knowing partisanship

	Neighbor PID				Contact Dems		Contact Reps		Comfort			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dem Exp	1.24	1.24			0.76	0.70			-0.10	-0.12		
	(0.14)	(0.10)			(0.34)	(0.18)			(0.23)	(0.13)		
HH Dem	-0.08	-0.05			0.10	0.04			-0.01	-0.05		
	(0.03)	(0.02)			(0.06)	(0.04)			(0.05)	(0.04)		
Dem Exp * Dem									0.62	0.55		
									(0.27)	(0.18)		
Rep Exp			-1.20	-1.28			1.59	1.67			-0.34	-0.48
			(0.13)	(0.12)			(0.29)	(0.18)			(0.23)	(0.16)
HH Rep			0.02	0.03			0.12	0.10			0.13	0.09
			(0.03)	(0.02)			(0.05)	(0.03)			(0.07)	(0.04)
Rep Exp * Rep											0.93	1.11
											(0.31)	(0.19)
BG White	-0.64	-0.47	-0.66	-0.48	0.03	-0.15	0.46	0.26	0.19	0.16	-0.04	0.10
	(0.14)	(0.11)	(0.15)	(0.11)	(0.32)	(0.20)	(0.27)	(0.18)	(0.21)	(0.13)	(0.19)	(0.12)
BG Age	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
BG Registered	0.29	0.19	0.33	0.20	-0.01	0.04	-0.07	-0.02	0.11	0.03	0.20	0.07
	(0.14)	(0.09)	(0.14)	(0.09)	(0.26)	(0.17)	(0.24)	(0.16)	(0.21)	(0.13)	(0.18)	(0.12)
BG Med. HH Income	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
BG College	0.51	0.41	0.55	0.43	0.64	0.78	0.00	0.18	0.17	-0.04	-0.04	0.07
	(0.15)	(0.12)	(0.15)	(0.12)	(0.36)	(0.24)	(0.29)	(0.21)	(0.26)	(0.17)	(0.26)	(0.17)
BG Homeowner	0.11	-0.02	0.13	0.01	-0.11	-0.23	-0.08	0.02	0.01	0.01	-0.16	-0.14
	(0.12)	(0.09)	(0.12)	(0.08)	(0.22)	(0.14)	(0.19)	(0.15)	(0.20)	(0.14)	(0.16)	(0.13)
BG Drive Work	0.18	0.12	0.20	0.13	-0.70	-0.31	-0.28	-0.16	-0.13	-0.21	0.18	-0.10
	(0.19)	(0.15)	(0.19)	(0.16)	(0.34)	(0.25)	(0.28)	(0.22)	(0.29)	(0.21)	(0.24)	(0.18)
BG Unemployed	0.53	0.34	0.56	0.39	0.10	-0.07	0.03	-0.19	1.48	0.62	1.11	0.24
	(0.36)	(0.25)	(0.36)	(0.25)	(0.72)	(0.43)	(0.56)	(0.43)	(0.54)	(0.33)	(0.52)	(0.34)
BG Med. House Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Asian	-0.02	-0.01	-0.05	-0.02	-0.69	-0.83	-0.73	-0.55	-0.23	-0.14	-0.44	-0.21
	(0.11)	(0.10)	(0.11)	(0.10)	(0.22)	(0.15)	(0.15)	(0.12)	(0.18)	(0.13)	(0.18)	(0.15)
Black	0.07	0.08	0.09	0.11	0.24	0.14	-0.33	-0.35	0.04	0.09	0.27	0.40
	(0.09)	(0.06)	(0.09)	(0.06)	(0.15)	(0.13)	(0.13)	(0.11)	(0.19)	(0.15)	(0.13)	(0.09)
Hispanic	-0.06	-0.11	-0.08	-0.12	-0.12	-0.14	-0.11	-0.09	-0.09	-0.09	-0.07	0.02
	(0.07)	(0.06)	(0.07)	(0.06)	(0.16)	(0.10)	(0.15)	(0.09)	(0.15)	(0.10)	(0.14)	(0.08)
White	-0.08	-0.09	-0.09	-0.09	-0.20	-0.25	-0.11	-0.04	-0.01	0.07	0.03	0.13
	(0.06)	(0.05)	(0.06)	(0.05)	(0.11)	(0.08)	(0.10)	(0.07)	(0.13)	(0.07)	(0.12)	(0.08)
Age	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	-0.01	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Male	0.01	0.00	0.01	0.00	0.06	0.01	0.02	0.03	0.22	0.18	0.05	0.05
	(0.03)	(0.02)	(0.03)	(0.02)	(0.06)	(0.04)	(0.05)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)
Liberalism	0.00	0.00	0.00	0.00	0.04	0.05	-0.11	-0.14	-0.02	-0.04	0.07	0.07
	(0.02)	(0.01)	(0.02)	(0.01)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Married	0.02	0.02	0.02	0.02	0.14	0.13	0.23	0.17	0.03	0.01	0.06	0.02
	(0.03)	(0.02)	(0.03)	(0.02)	(0.09)	(0.05)	(0.06)	(0.05)	(0.05)	(0.04)	(0.05)	(0.03)
College	-0.03	-0.01	-0.03	-0.01	0.25	0.25	0.10	0.11	-0.04	-0.06	0.00	-0.05
	(0.03)	(0.02)	(0.03)	(0.02)	(0.06)	(0.04)	(0.06)	(0.04)	(0.05)	(0.03)	(0.06)	(0.03)
Years Residence	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Party7	0.03	0.01	0.03	0.01	0.03	0.04	-0.11	-0.08	-0.03	-0.03	0.04	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
Num.Obs.	19,123	19,123	19,123	19,123	18,144	18,144	18,159	18,159	14,365	14,365	14,365	14,365
R^2	0.600	0.507	0.599	0.507	0.407	0.268	0.469	0.323	0.440	0.261	0.444	0.266
R^2 Adj.	0.511	0.396	0.509	0.396	0.267	0.096	0.344	0.164	0.274	0.042	0.279	0.048

Table S11: Full survey results – Perception of Democratic and Republican Party ideology and favorability toward Democrats and Republicans

	Democrat Ideology		Republican Ideology		Democrat Thermometer		Republican Thermometer	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dem Exp	-0.03	-0.11			1.98	4.21		
	(0.15)	(0.08)			(3.39)	(2.06)		
HH Dem	-0.08	-0.09			2.72	2.76		
	(0.03)	(0.02)			(0.55)	(0.34)		
Rep Exp			0.02	-0.04			3.92	4.30
			(0.16)	(0.09)			(2.42)	(1.81)
HH Rep			0.00	0.05			2.83	2.35
			(0.03)	(0.02)			(0.55)	(0.39)
BG White	0.09	-0.06	-0.17	-0.06	-0.02	1.11	-0.29	1.16
	(0.14)	(0.08)	(0.18)	(0.09)	(2.65)	(1.75)	(2.51)	(1.71)
BG Age	0.00	0.00	0.00	0.00	0.01	0.00	-0.03	-0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.05)	(0.03)	(0.05)	(0.03)
BG Registered	0.07	0.07	0.08	-0.05	0.50	1.18	-1.48	-1.87
	(0.12)	(0.07)	(0.15)	(0.09)	(2.60)	(1.78)	(2.82)	(1.71)
BG Med. HH Income	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
BG College	0.04	0.03	-0.30	-0.19	0.47	1.49	0.91	-1.20
	(0.17)	(0.10)	(0.19)	(0.11)	(3.25)	(1.90)	(2.87)	(2.11)
BG Homeowner	0.18	0.08	-0.16	-0.07	-1.94	-1.22	-0.92	-1.30
	(0.14)	(0.07)	(0.13)	(0.08)	(2.13)	(1.51)	(2.72)	(1.45)
BG Drive Work	0.08	0.11	0.25	0.14	2.59	3.28	4.37	4.33
	(0.23)	(0.12)	(0.29)	(0.15)	(3.61)	(2.43)	(4.07)	(3.02)
BG Unemployed	-0.16	0.02	0.09	-0.04	1.11	-0.28	-1.74	5.08
	(0.42)	(0.21)	(0.45)	(0.23)	(8.20)	(4.29)	(9.02)	(5.28)
BG Med. House Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Asian	-0.04	-0.05	0.04	-0.13	0.93	4.97	3.00	1.08
	(0.13)	(0.07)	(0.14)	(0.07)	(2.00)	(1.64)	(1.83)	(1.28)
Black	-0.14	-0.25	-0.08	-0.02	5.84	9.52	0.96	-0.15
	(0.10)	(0.08)	(0.13)	(0.08)	(1.78)	(1.39)	(1.79)	(1.24)
Hispanic	-0.08	-0.15	-0.15	-0.11	2.48	4.37	2.80	1.41
	(0.12)	(0.06)	(0.10)	(0.07)	(1.96)	(1.30)	(1.47)	(1.19)
White	0.11	0.02	-0.30	-0.27	0.76	2.90	2.02	0.52
	(0.08)	(0.05)	(0.09)	(0.05)	(1.31)	(1.07)	(1.29)	(0.83)
Age	0.00	0.00	0.00	0.00	0.13	0.12	0.06	0.07
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.03)	(0.02)
Male	0.07	0.03	-0.01	0.00	-2.43	-2.21	-3.02	-3.07
	(0.03)	(0.02)	(0.04)	(0.02)	(0.65)	(0.37)	(0.51)	(0.34)
Liberalism	-0.15	-0.15	-0.08	-0.10	4.61	5.34	-5.25	-5.74
	(0.02)	(0.01)	(0.02)	(0.01)	(0.28)	(0.22)	(0.31)	(0.20)
Married	0.06	0.05	0.02	0.00	0.83	0.16	0.25	-0.10
	(0.03)	(0.02)	(0.04)	(0.03)	(0.88)	(0.50)	(0.72)	(0.49)
College	0.05	0.04	-0.21	-0.14	1.62	1.70	-1.98	-2.12
	(0.04)	(0.02)	(0.04)	(0.02)	(0.67)	(0.43)	(0.64)	(0.40)
Years Residence	0.00	0.00	0.00	0.00	-0.03	-0.01	0.02	0.02
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.01)	(0.02)	(0.01)
Party7	-0.15	-0.16	-0.11	-0.10	9.64	9.06	-8.91	-8.55
	(0.01)	(0.01)	(0.01)	(0.01)	(0.21)	(0.15)	(0.23)	(0.16)
Num.Obs.	21,159	21,159	21,144	21,144	18,886	18,886	18,850	18,850
R^2	0.554	0.428	0.456	0.296	0.800	0.774	0.782	0.752
R^2 Adj.	0.463	0.311	0.345	0.152	0.754	0.722	0.733	0.696

The dissimilarity index is a measure of geographic evenness between two groups (most commonly used to measure Black-White racial segregation), comparing the composition of sub-geographies (generally Census tracts) to larger geographies (often counties or cities). The dissimilarity index ranges from 0 (complete integration) to 1 (complete segregation) the proportion of a group that would have to move to achieve complete integration. Dissimilarity thus whether, conditional on the overall partisan composition of a county, how segregated Democrats and Republicans are across Census tracts within that county. The Democrat-Republican dissimilarity index is formalized as:

$$DI_c = \frac{1}{2} \sum_{t=1}^{N_t} \left| \frac{D_t}{D_c} - \frac{R_t}{R_c} \right|$$

where DI_c is the dissimilarity index for county c, D_t and R_t are the number of Democrats and Republican in tract t, and D_c and R_c are the number of Democrats and Republicans in county c, and N_t is the number of tracts in the county.

While the dissimilarity index captures segregation within counties, the county-level share of the electorate that is Democrat versus Republicans captures in absolute terms the partisan balance of each county. Analysis of this metric allows for tests of the extent to which social influence is making counties more Democratic or more Republican. The relative share is formalized as:

$$DR_c = \frac{\sum_{i \in c} D_i}{\sum_{i \in c} D_i + \sum_{i \in c} R_i}$$

where DR_c is the proportion of Democrats out of total Democrats and Republicans in county c, and D_i and R_i are indicator variables that take a value of 1 if voter i is a Democrat or Republican.

Party switching was simulated by fitting the current effect main specification to the 2012-2020 linked sample, and then simulating party switching with that fitted model but the with the coefficients on partisan exposure set to zero. Similar to the main analysis, separate models were fit based on starting partisanship (2012 Democrats, Republicans, and Non-partisans), and the effect of Democratic exposure on Democratic partisanship and Republican exposure on Republican partisanship were estimated in separate models. For each voter in the linked sample, the probabilities of being a Democrat and Republican in 2020 were generated from the appropriate specification. These two probabilities were then input into a draw from a categorical distribution with three outcomes

Table S12: County Dissimilarity Index Simulation Summary Statistics

	2012 Actual	2020						Actual vs. Simulation	
		Actual			Simulation				
	DI	DI	Δ	% Δ	DI	Δ	% Δ	Diff.	% Explained
	0.234	0.246	0.012	4.997%	0.245	0.011	4.491%	0.001	10.137%

Table shows the county dissimilarity index in the actual data and in the simulation without social influence. The final two columns show the difference between the actual and simulated 2012-2020 change, and the percent of the actual change that is explained by social influence, calculated by dividing the difference between the actual and simulate change (column 11) by the actual change (column 8).

(2020 Democrat, Republican, or Non-partisan). The drawing process was repeated 100 times to create 100 simulation data sets. For each simulated dataset, the party switchers were merged to the entire list of voters in each state in 2020, and the dissimilarity index and relative Democratic share were calculated for each county. I also calculated the relative Democratic share for each Census tract.

Table S12 shows the average dissimilarity index across counties, weighted by registered voters in the county. From 2012 to 2020, the average dissimilarity index rose by 1.17 percentage points, a 5% increase.[6] Comparing this ground truth to the simulated results demonstrates that social influence accounted for 10.137% of this increase, as the actual increase is 0.12 percentage points less than the simulated increase without social influence. Thus, partisan segregation within counties increased moderately over the past 8 years, and social influence is responsible for a modest portion of this increase.

To examine how social influence is making areas more Democratic or Republican in absolute terms, I classify counties as more Democratic than Republican (or vice-versa) in 2012. I then measure in the simulation the extent to which social influence effects had an impact on these counties trajectories, and how social influence contributes to the difference between Democratic and Republican counties across time. Table S13 displays the weighted average of relative Democratic share across counties, weighted by registered voters, separately for Democratic and Republican counties. From 2012 to 2020, Democratic counties increased their relative Democratic share by 3.2 percentage points. Republican counties in the 5 states of the study actually became more Democratic from 2012-2020, albeit at a smaller rate than Democratic counties, increasing their

[6] This increase mostly occurred in the 2012-2016 period. From 2016-2020, the dissimilarity index remained stagnant.

Table S13: Relative Democratic Share Simulation Statistics

			2012	2020						Actual vs.	
			Actual		Actual			Simulation		Simulation	
Unit	Type	N	Share	Share	Δ	% Δ	Share	Δ	% Δ	Diff.	% Explained
County	Dem.	160	0.658	0.690	0.032	4.858%	0.689	0.031	4.71%	0.001	3.037%
County	Rep.	232	0.427	0.447	0.0199	4.651%	0.447	0.020	4.685%	-0.0001	-0.74%
County	Dem. - Rep.	-	0.231	0.242	0.012	5.241%	0.242	0.011	4.757%	0.001	9.237%
Tract	Dem.	12,793	0.710	0.741	0.030	4.258%	0.740	0.029	4.109%	0.0001	3.497%
Tract	Rep.	7,174	0.390	0.412	0.022	5.716%	0.412	0.022	5.749%	-0.0001	-0.583%
Tract	Dem. - Rep.	-	0.320	0.328	0.008	2.483%	0.327	0.007	2.112%	0.001	14.930%

Table shows the proportion Democrat (out of all Democrats and Republicans) in the actual data and in the simulation without social influence. The final two columns show the difference between the actual and simulated 2012-2020 change, and the percent of the actual change that is explained by social influence, calculated by dividing the difference between the actual and simulate change (column 11) by the actual change (column 6). The Dem. - Rep. columns show the difference in relative Democratic share between counties (tracts) that had more Democrats than Republicans in 2012 and counties (tracts) that had more Republicans than Democrats in 2012, demonstrating how social influence has contributed to the difference in demographics between Democratic and Republican counties (tracts).

relative Democratic share by 2.0 percentage points. In the Democrat counties, social influence accounted for 3.037% of the increase, with the simulated results having an average Democratic share 0.1 percentage points lower than the actual changes. In Republican counties, social influence worked to reduce the observed increase in Democratic share: simulation shows that without social influence the increase in Democratic share would have been even larger. Trends in polarization across counties can be best understood by looking at the change in the average relative Democratic share between Democratic and Republican counties. In 2012, majority Democratic counties had a 0.231 higher relative Democratic share than majority Republican counties. By 2020, the gap between these same counties had risen to 0.242. Simulation results show that social influence contributed to 9.237% of this gap. Therefore, social influence is also contributing to polarization across counties. Table S13 also shows the relative Democratic share comparison by Census tract, demonstrating a similar impact of social influence on the demographic trajectory of these smaller geographies.