Supporting Information for "Partisan Conversion through Neighborhood Influence"

Contents

Table S1: State Voterfiles

State	Year
CA	2005, 2007, 2009, 2012-2020
FL	2007, 2009, 2012-2020
KS	2008, 2012-2020
NC	2009, 2012-2020
NY	2001, 2008, 2012-2020

1 Voterfile Data and Panel Construction

Data for this study consists of yearly TargetSmart 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). TargetSmart 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. Table S1 lists the data availability for each state and year. 2012-2020 files come from TargetSmart, pre-2012 files from the states.

I take the following initial cleaning steps when constructing the analysis samples. First, I use TargetSmart's field on whether a voter is found in the Social Security Death records to drop voters that are deceased. Second, I de-duplicate records with the same exact track ID (TargetSmart's identifier across years), first name, and last name, giving preference to the record whose registration status is "Registered" (vs. "Unregistered"), voter status is "Active" (vs. "Inactive," based on recent election participation), and with the most recent registration date. I then proceed to link TargetSmart data across years, relying on their linkages for the 2012-2020 samples (see Section S8 for robustness of results to alternative sample construction strategies).

To construct the longer panel, I link pre-2012 files directly to the TargetSmart files by

Table S2: 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	45.580	51.892	46.532
Democrat	0.408	0.447	0.435	0.433	0.431	0.429
Republican	0.369	0.303	0.335	0.278	0.303	0.270
White	0.764	0.553	0.702	0.638	0.664	0.652
Black	0.082	0.114	0.093	0.112	0.104	0.116
Hispanic	0.091	0.119	0.122	0.141	0.151	0.153
Asian	0.033	0.032	0.042	0.040	0.047	0.041
Female	0.538	0.538	0.536	0.524	0.538	0.542
Block Group Democrat	0.400	0.450	0.425	0.444	0.428	0.433
Block Group Republican	0.361	0.310	0.321	0.300	0.294	0.283
Block Group White	0.652	0.571	0.593	0.559	0.565	0.550
Block Group Registered	0.615	0.618	0.515	0.497	0.610	0.603
Block Group Median Age	40.626	39.234	40.571	39.358	41.148	40.066
Block Group Median Household Income	69,496.741	61,572.561	69,544.197	63,627.708	70,521.308	64,695.522
Block Group Median Year House Built	1,973.970	1,970.390	1,971.584	1,971.303	1,972.923	1,974.423
Block Group Median House Value	343,528.344	363,855.688	339,896.906	329,663.242	356,219.866	333,231.984
Block Group Homeowner	0.752	0.605	0.687	0.607	0.649	0.587
Block Group Drive to Work	0.886	0.791	0.833	0.798	0.814	0.815
Democratic Exposure	0.402	0.453	0.423	0.442	0.429	0.434
Republican Exposure	0.357	0.302	0.309	0.281	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.

first exact matching on first name, last name, birth year, and residential address. Next, I match only on first name, last name, and residential address, to see if there are any potential links where age was differentially recorded. Last, in order to account for potential surname changes, possibly due to marriage, I link the remaining unlinked sample by first name, birth year and residential address.

Table S2 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 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.

Table S3: Correlation between precinct and county presidential vote share and partisan registration

	Precinct		County	
Year	Democratic	Republican	Democratic	Republican
2012	0.88	0.92	0.87	0.93
2016	0.87	0.90	0.88	0.90
2020	0.90	0.91	0.92	0.95

Table shows correlations between Democratic (Republican) presidential vote share and proportion registered Democrat (Republican) at the precinct and count-levels. Correlations are weighted by the number of registered voters in the precinct or county.

Table S4: Partisan Differences in Old and New Neighborhoods for Movers

	2012-2016				2016-2020			
	Prop. Democrat		Prop. Republican		Prop. Democrat		Prop. 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.

2 Mover Analysis

Tables S4 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 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:

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

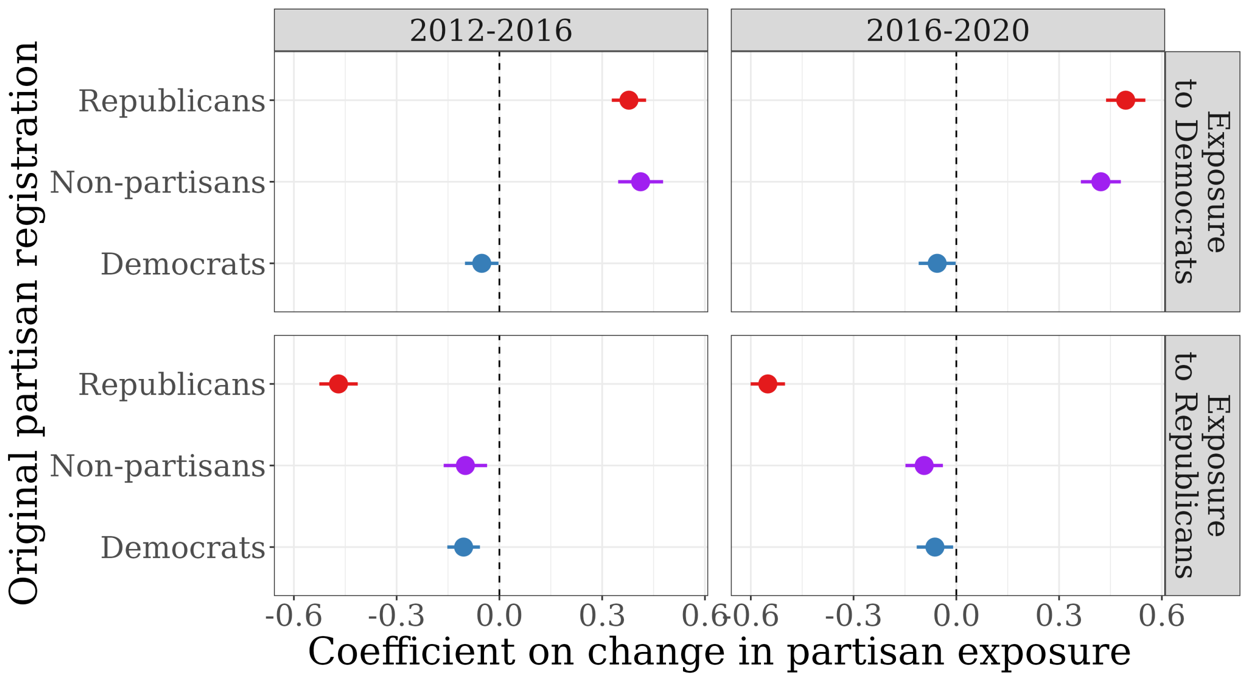


Figure S1: Effect of Census Block Group Changes in Partisan Exposure on Moving

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

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.

Table S5: 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	0.047	0.043
Democratic	Republicans	0.061	0.052	0.054	0.051	0.051
Republican	Republicans	0.069	0.059	0.061	0.055	0.053
Democratic	Non-Partisans	0.064	0.055	0.060	0.054	0.055
Republican	Non-Partisans	0.061	0.050	0.052	0.050	0.049

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 this for the pre-trend specification strata. I report the average within-strata standard deviations in Table S5, showing that there is variation within strata in changes in partisan exposure, making the within Zip Code and other characteristic comparison feasible.

4 Estimation and Identifying Assumptions

There are several threats to inference that must be considered in order to interpret the estimates in this paper causally. First, many things besides partisan composition are changing in neighborhoods. If these trends correlate with trends in partisan exposure and registration, they may confound the effects. I address this concern in the estimation by focusing on non-movers and accounting for other time-variant features of neighborhoods.

Second, voters who live with different levels of partisan exposure and who see different changes in partisan exposure over time may differ along characteristics that influence their partisan registration. Put another way, pre trends in partisanship or partisan geography may not be parallel: voters who see different changes in partisan exposure were already trending away from each other prior to the period of study. Such ongoing processes of partisan realignment – operating through race, class, education and other demographic characteristics – likely contribute to ongoing trends in geographic polarization. If these trends are not accounted for then contextual effects cannot be separated from spatially-concentrated but context-independent realignments.

I take several steps to address this concern. First, as discussed previously, I match on individual and contextual variables to narrow the scope of my comparison to compare most similar individuals. In the results section, I present pre-trend placebo analyses that demonstrate that with this estimation strategy changes in partisan exposure during treatment periods are not predictive of partisanship in any of the years in the data prior to the treatment period.

Incorporating household partisan composition into the matching strategy and controlling for household-level changes strengthens the inference of neighbor influence, in that it further restricts the scope of potential confounding shocks to those that operate commonly across neighbors but not commonly across household members. Any household-level shocks to partisanship are accounted for in the estimation and will not bias the neighbor exposure coefficients. For localized shocks to threaten inference, they would have to be influencing voters and their neighbors, but not their household members, as well as being independent from the other matching criteria and contextual controls. For example, the effect of local economic events on partisanship are likely accounted for by this estimation, since most external economic impacts (even those that are operating within-Zip Code and independently of race, age, gender, and starting partisan exposure) are experienced equally by household members.

Table S6: 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
2008-2012	Female	0.587	0.597	0.510	0.542	0.502	0.488
2008-2012	White	0.655	0.618	0.882	0.832	0.769	0.772
2008-2012	2008 Dem. Exp.	0.475	0.430	0.336	0.364	0.380	0.386
2008-2012	2008 Rep. Exp.	0.296	0.321	0.428	0.404	0.348	0.371
2008-2012	Δ Dem. Exp.	-0.007	0.013	-0.005	-0.016	-0.002	-0.008
2008-2012	Δ Rep. Exp.	-0.020	-0.032	-0.027	-0.010	-0.025	-0.029
2008-2012	Block Group White	0.589	0.564	0.714	0.689	0.669	0.655
2008-2012	Block Group Med. HH Inc.	65,726	69,611	72,505	67,655	71,580	70,257
2008-2012	Block Group Homeowner	0.724	0.726	0.782	0.770	0.755	0.754
2012-2016	Age	54	48	56	55	49	51
2012-2016	Female	0.587	0.542	0.505	0.511	0.495	0.465
2012-2016	White	0.578	0.597	0.857	0.823	0.708	0.721
2012-2016	2012 Dem. Exp.	0.503	0.456	0.337	0.364	0.400	0.408
2012-2016	2012 Rep. Exp.	0.243	0.271	0.395	0.370	0.304	0.319
2012-2016	Δ Dem. Exp.	-0.004	0.015	-0.005	-0.015	-0.003	-0.008
2012-2016	Δ Rep. Exp.	-0.014	-0.022	-0.014	0.001	-0.015	-0.018
2012-2016	Block Group White	0.514	0.519	0.688	0.662	0.614	0.600
2012-2016	Block Group Med. HH Inc.	65,014	68,677	72,504	67,789	70,731	69,196
2012-2016	Block Group Homeowner	0.638	0.642	0.748	0.734	0.694	0.696
2016-2020	Age	52	48	56	53	47	49
2016-2020	Female	0.592	0.567	0.505	0.498	0.498	0.499
2016-2020	White	0.525	0.612	0.859	0.767	0.668	0.630
2016-2020	2016 Dem. Exp.	0.516	0.443	0.327	0.368	0.404	0.427
2016-2020	2016 Rep. Exp.	0.215	0.262	0.386	0.339	0.281	0.281
2016-2020	Δ Dem. Exp.	0.001	0.021	0.001	-0.007	0.003	0.002
2016-2020	Δ Rep. Exp.	-0.011	-0.022	-0.010	0.002	-0.011	-0.021
2016-2020	Block Group White	0.478	0.526	0.680	0.613	0.582	0.522
2016-2020	Block Group Med. HH Inc.	66,993	78,207	73,618	70,964	71,213	76,087
2016-2020	Block Group Homeowner	0.590	0.637	0.727	0.700	0.656	0.655

5 Descriptive Statistics and Main Results Tables

Table S6 presents average levels of descriptive variables for voters by partisan stability or partisan switching across the linked samples. Table S7 shows these statistics by levels of changes in Democratic and Republican exposure. Table S8 presents the full regression tables from the current effect main specifications.

Table S7: 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	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	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

6 Additional Panel Results

6.1 Age and Housing Results

Next I show the age and housing results 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.

Table S8: 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	0.039***	0.075***	0.062***	0.033***	0.085***	0.056***	0.073***	0.176***	0.093***
	(0.004)	(0.008)	(0.005)	(0.003)	(0.009)	(0.004)	(0.006)	(0.011)	(0.005)
Δ HH Democrats	0.064***	0.065***	0.102***	0.059***	0.065***	0.093***	0.115***	0.122***	0.097***
	(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***	−0.069***
	(0.001)	(0.001)	(0.006)	(0.000)	(0.002)	(0.009)	(0.001)	(0.003)	(0.006)
ΔBG White	−0.001	0.002	0.001	−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	−0.001
	(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	−0.005	−0.003+	0.001	0.000	0.000	−0.002	0.000	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***	−0.011***	−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	0.006	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	8 205 468	6 913 541	10 743 631
R2	0.503	0.565	0.450	0.536	0.567	0.479	0.490	0.506	0.440
R2 Adj.	0.220	0.133	0.103	0.200	0.091	0.112	0.175	0.097	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***	0.065***	0.034***	0.085***	0.068***	0.070***	0.112***	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***	0.117***	0.150***	0.057***	0.147***	0.166***	0.099***	0.137***	0.171***
	(0.003)	(0.012)	(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	0.002*	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 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	0.004	−0.001	−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 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				−0.005***	0.009***	0.004***	0.006+	−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	0.001	0.003	0.000
				(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Δ BG Unemployed				0.002	−0.001	−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	8 205 468	6 913 541	10 743 631
R2	0.475	0.561	0.461	0.517	0.578	0.483	0.487	0.509	0.455
R2 Adj.	0.138	0.130	0.156	0.119	0.127	0.162	0.125	0.115	0.173

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Outcome	Years	Exposure	Starting party	Effect of 10 p.p. increase	Baseline probability of outcome	Percentage increase
Democrat	2008-2012	Democratic	Democrat	0.0062	0.9600	0.6%
Democrat	2008-2012	Democratic	Non-Partisan	0.0075	0.0410	18.3%
Democrat	2008-2012	Democratic	Republican	0.0039	0.0180	21.9%
Republican	2008-2012	Republican	Democrat	0.0065	0.0240	27.3%
Republican	2008-2012	Republican	Non-Partisan	0.0070	0.0370	18.9%
Republican	2008-2012	Republican	Republican	0.0046	0.9630	0.5%
Democrat	2012-2016	Democratic	Democrat	0.0056	0.9690	0.6%
Democrat	2012-2016	Democratic	Non-Partisan	0.0085	0.0350	24.4%
Democrat	2012-2016	Democratic	Republican	0.0033	0.0130	25%
Republican	2012-2016	Republican	Democrat	0.0068	0.0170	39.7%
Republican	2012-2016	Republican	Non-Partisan	0.0085	0.0300	28.3%
Republican	2012-2016	Republican	Republican	0.0034	0.9710	0.4%
Democrat	2016-2020	Democratic	Democrat	0.0093	0.9430	1%
Democrat	2016-2020	Democratic	Non-Partisan	0.0176	0.0840	20.9%
Democrat	2016-2020	Democratic	Republican	0.0073	0.0300	24.3%
Republican	2016-2020	Republican	Democrat	0.0100	0.0250	40%
Republican	2016-2020	Republican	Non-Partisan	0.0112	0.0450	24.9%
Republican	2016-2020	Republican	Republican	0.0070	0.9370	0.7%

Table S9: Current effects compared to baseline probabilities of switching parties

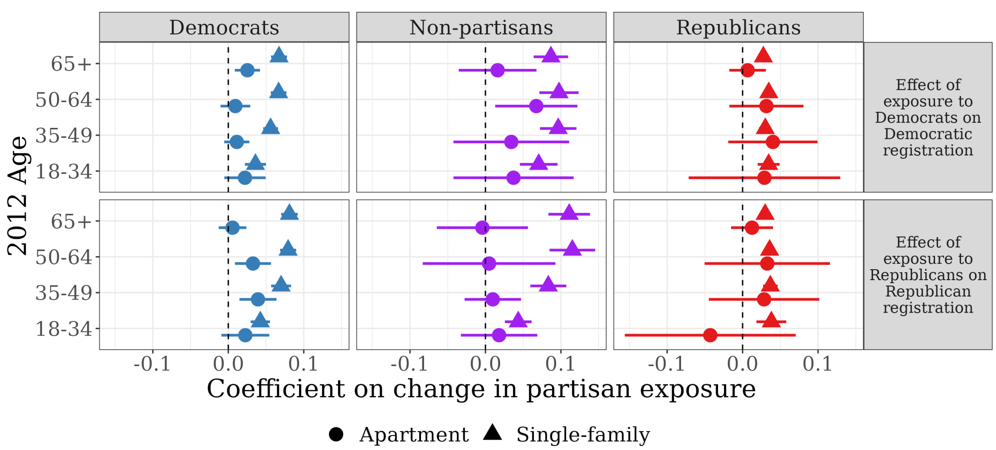


Figure S2: Effect of Partisan Exposure by Age and Housing Type – 2012-2016

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 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.

Figures S4 and S5 shows the downstream effects subset by age and housing type, and those subsets on White voters only.

Table S10: Downstream Effects Main Specification Regression Tables

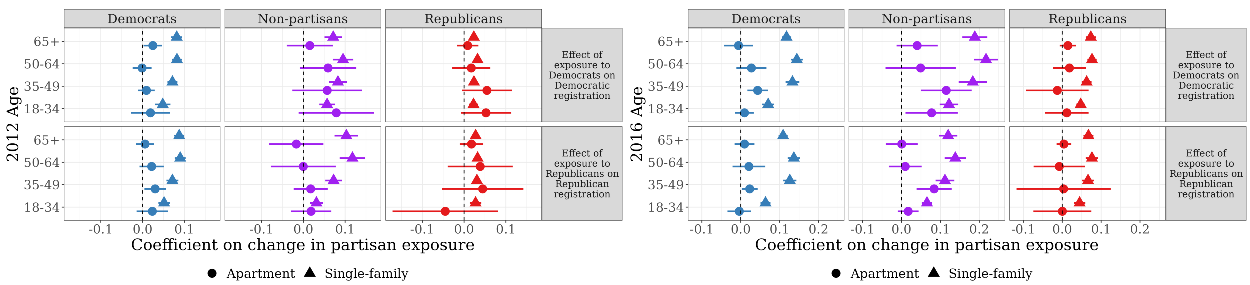
DV: Δ Dem. Reg.	EV: 2008-2012 DV: 2012-2016			EV: 2012-2016 DV: 2016-2020		
	'08-'12 Reps	'08-'12 NPs	'08-'12 Dems	'12-'16 Reps	'12-'16 NPs	'12-'16 Dems
Δ Dem Exp	0.011***	0.027***	0.027***	0.034***	0.066***	0.052***
	(0.002)	(0.004)	(0.003)	(0.005)	(0.010)	(0.004)
Δ HH Democrats	0.018***	0.017***	0.019***	0.046***	0.050***	0.033***
	(0.001)	(0.002)	(0.001)	(0.004)	(0.004)	(0.002)
Δ HH Voters	−0.001***	−0.002***	−0.015***	−0.004***	−0.007***	−0.022***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Δ BG White	0.002*	−0.001	0.001	0.002	−0.001	0.000
	(0.001)	(0.005)	(0.003)	(0.001)	(0.004)	(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)
Δ BG Reg	0.000	−0.003	−0.001	0.001	−0.003	0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(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)
Δ BG Homeowner	−0.002+	0.001	0.002	−0.001	0.006	0.001
	(0.001)	(0.004)	(0.002)	(0.002)	(0.004)	(0.002)
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)
Δ BG Drive Work	0.001	−0.002	0.000	−0.001	−0.005	0.000
	(0.002)	(0.005)	(0.002)	(0.002)	(0.005)	(0.002)
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)
Δ Married				−0.002*	0.003	−0.012***
				(0.001)	(0.003)	(0.001)
Δ BG College				−0.001	−0.003	−0.003
				(0.002)	(0.005)	(0.003)
Δ BG Unemployed				0.002	0.008	−0.001
				(0.002)	(0.008)	(0.003)
Num.Obs.	4 265 401	2 372 121	4 696 265	4 928 638	3 117 990	6 078 691
R2	0.521	0.623	0.480	0.557	0.620	0.537
R2 Adj.	0.179	0.125	0.064	0.154	0.071	0.127

DV: Δ Rep. Reg.	EV: 2008-2012 DV: 2012-2016			EV: 2012-2016 DV:2016-2020		
	'08-'12 Reps	'08-'12 NPs	'08-'12 Dems	'12-'16 Reps	'12-'16 NPs	'12-'16 Dems
Δ Rep Exp	0.016***	0.026***	0.029***	0.036***	0.051***	0.052***
	(0.002)	(0.005)	(0.003)	(0.005)	(0.009)	(0.004)
Δ HH Republicans	0.017***	0.023***	0.030***	0.040***	0.050***	0.055***
	(0.001)	(0.003)	(0.002)	(0.005)	(0.004)	(0.003)
Δ HH Voters	−0.012***	−0.002***	−0.002***	−0.026***	−0.007***	−0.004***
	(0.001)	(0.001)	(0.000)	(0.003)	(0.001)	(0.001)
Δ BG White	−0.002	−0.001	−0.001	0.003	0.002	−0.002
	(0.002)	(0.004)	(0.002)	(0.002)	(0.003)	(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)
Δ BG Reg	0.000	0.004+	0.001	0.000	0.002	0.000
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(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)
Δ BG Homeowner	0.006*	−0.004	−0.002	0.000	0.002	0.000
	(0.002)	(0.004)	(0.002)	(0.002)	(0.003)	(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)
Δ BG Drive Work	0.000	0.000	0.001	0.000	0.003	−0.001
	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)	(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)
Δ Married				−0.004***	0.009***	0.005***
				(0.001)	(0.001)	(0.001)
Δ BG College				0.000	0.000	0.003
				(0.002)	(0.003)	(0.002)
Δ BG Unemployed				−0.006	−0.003	−0.002
				(0.004)	(0.005)	(0.002)
Num.Obs.	4 265 401	2 372 121	4 696 265	4 928 638	3 117 990	6 078 691
R2	0.498	0.597	0.468	0.563	0.633	0.532
R2 Adj.	0.090	0.070	0.090	0.107	0.118	0.169

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Outcome	Treatment Years	Outcome Years	Exposure	Starting party	Effect of 10 p.p. increase	Baseline probability of outcome	Percentage increase
Democrat	2008-2012	2012-2016	Democratic	Democrat	0.0027	0.9690	0.3%
Democrat	2008-2012	2012-2016	Democratic	Non-Partisan	0.0027	0.0350	7.7%
Democrat	2008-2012	2012-2016	Democratic	Republican	0.0011	0.0130	8.4%
Republican	2008-2012	2012-2016	Republican	Democrat	0.0029	0.0170	17.3%
Republican	2008-2012	2012-2016	Republican	Non-Partisan	0.0026	0.0300	8.7%
Republican	2008-2012	2012-2016	Republican	Republican	0.0016	0.9710	0.2%
Democrat	2012-2016	2016-2020	Democratic	Democrat	0.0052	0.9430	0.6%
Democrat	2012-2016	2016-2020	Democratic	Non-Partisan	0.0066	0.0840	7.9%
Democrat	2012-2016	2016-2020	Democratic	Republican	0.0034	0.0300	11.3%
Republican	2012-2016	2016-2020	Republican	Democrat	0.0052	0.0250	20.8%
Republican	2012-2016	2016-2020	Republican	Non-Partisan	0.0051	0.0450	11.2%
Republican	2012-2016	2016-2020	Republican	Republican	0.0036	0.9370	0.4%

Table S11: Downstream effects compared to baseline probabilities of switching parties



(a) 2012-2016

(b) 2016-2020

Figure S3: Effect of Partisan Exposure by Age and Housing Type – White Voters

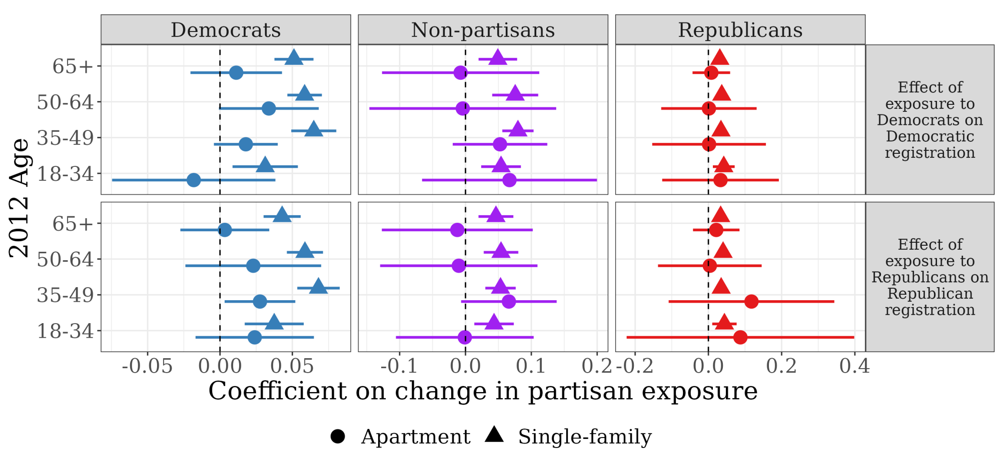


Figure S4: Effect of Partisan Exposure by Age and Housing Type – 2012-2016 downstream effects

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 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.

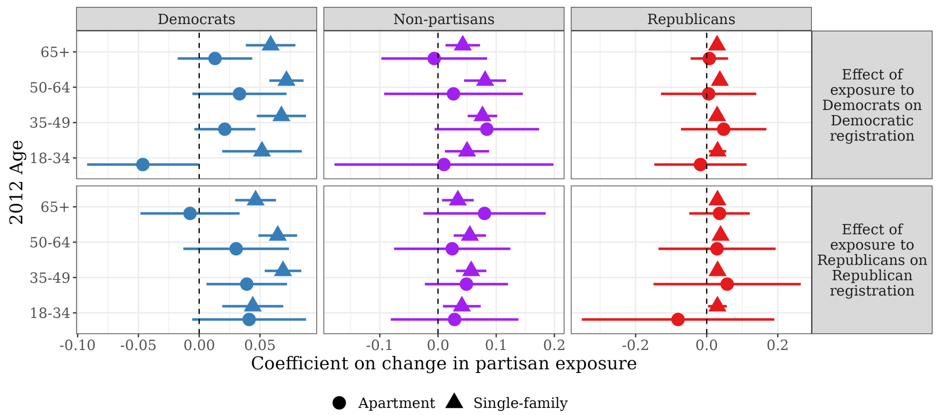


Figure S5: Effect of Partisan Exposure by Age and Housing Type – White Voters, 2012-2016 downstream effects

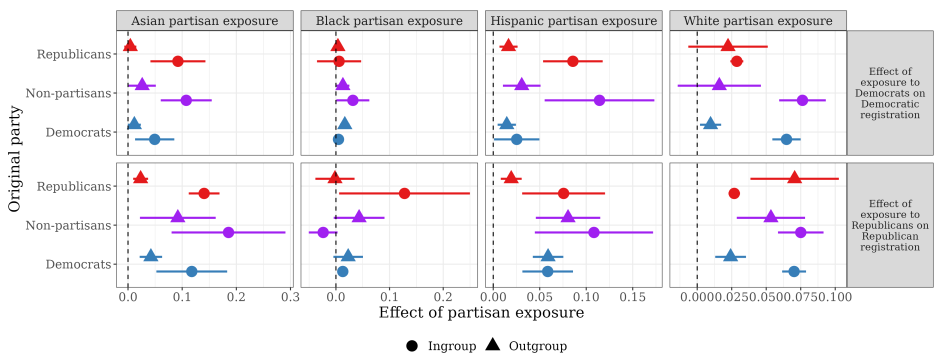


Figure S6: Voters are Most Influenced by Same-Race Neighbors - 2012-2016 sample

First panel from left plots effect of exposure to White Democrats or White Republicans, from the current effect specifications for the 2012-2016 linked sample. Points are plotted separately for in-group and out-group voters. The other panels 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.

6.2 Same-race neighbor results

Here, I present the 2012-2016 linked sample results for exposure to same-race Democratic or Republican neighbors.[2] Figure S6 plots the results.

[2]The models for the race subset results are of the form:

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

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. The exposure effects by each race subset are extracted from these interaction models.

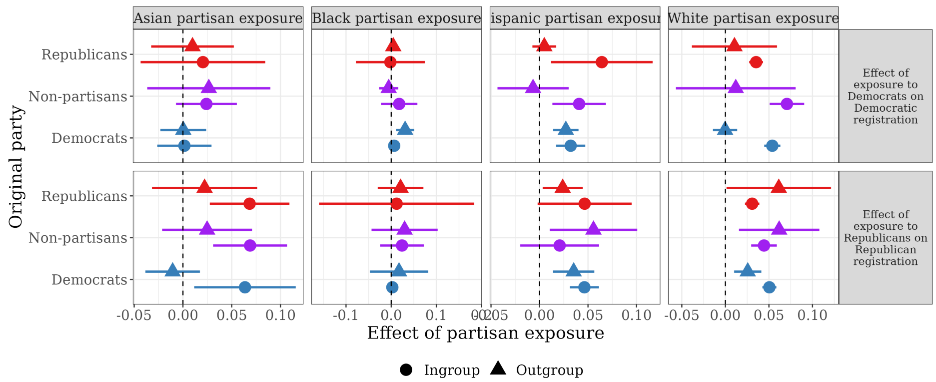


Figure S7: Voters are Most Influenced by Same-Race Neighbors – downstream effects

First panel from left plots effect of exposure to White Democrats or White Republicans, from the current effect specifications for the 2012-2016 linked sample. Points are plotted separately for in-group and out-group voters. The other panels 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.

Next, in Figure S7 I present the race subset results for the downstream effects.

6.3 Downstream effects by district

6.4 Main Results Across Other Time Periods and by State

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

6.5 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 effects specification in the manuscript. I present these results for the 2012-2016 and 2016-2020 linked samples. These include:

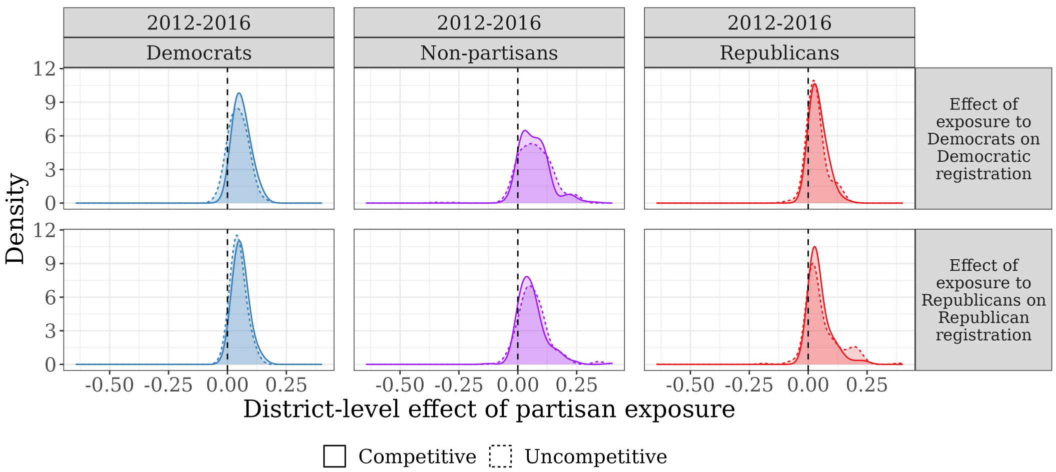
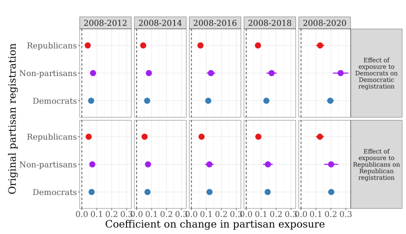
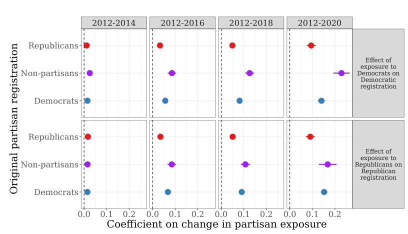


Figure S8: District Electoral Competition is not Determinant of Effect Size – downstream effects

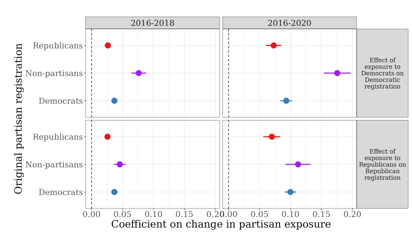
Figure plots the distribution of current effects across U.S. House districts for the 2012-2016 and 2016-2020 linked samples. Distributions are weighted by voters in the sample in each district. Distributions are plotted separately for year 1 Democrats (blue), Republicans (red) and Non-Partisans (purple) 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).



(a) 2008 samples



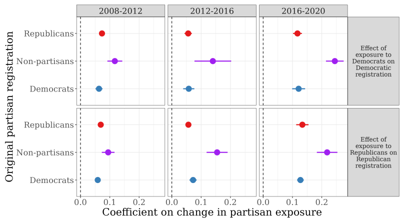
(b) 2012 samples



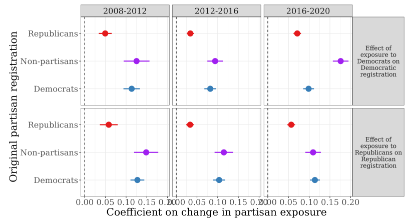
(c) 2016 samples

Figure S9: Effect of Partisan Exposure Across Multiple Time Periods

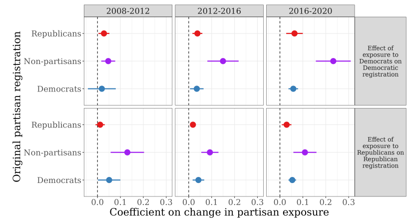
Figure plots the effect of Democratic and Republican exposure across alternative linked samples. Results are plotted separately based on partisanship in the first year of each linked sample.



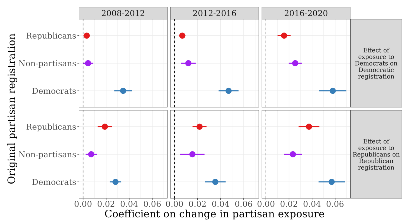
(a) CA



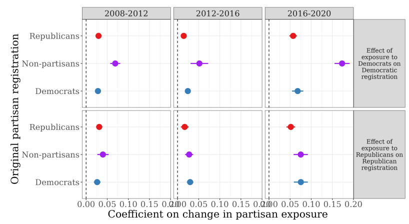
(b) FL



(c) KS



(d) NC



(e) NY

Figure S10: 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.

1. Aspatial exposure, the proportion of Democrats or Republicans in each voter's 1,000 nearest 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, not weighted by distance).
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.[3]
9. Main specification without Census Block Group controls

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

Table S12: Alternative Treatment Estimates – current effects

	Current effects: 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	0.052	0.119	0.151	0.043	0.141
	(0.01)	(0.004)	(0.013)	(0.009)	(0.005)	(0.008)
Aspatial	0.021	0.017	0.049	0.019	0.009	0.027
	(0.005)	(0.006)	(0.014)	(0.006)	(0.006)	(0.01)
Dem. Ratio	0.063	0.025	0.053	-0.053	-0.035	-0.061
	(0.004)	(0.003)	(0.006)	(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	0.03	0.074
	(0.004)	(0.003)	(0.008)	(0.003)	(0.003)	(0.008)
Mile Radius	0.053	0.029	0.08	0.062	0.03	0.077
	(0.004)	(0.003)	(0.009)	(0.004)	(0.003)	(0.009)
New Neighbors	0.008	0.014	0.042	0.023	0.011	0.038
	(0.004)	(0.006)	(0.012)	(0.006)	(0.006)	(0.01)
Census Block	0.001	0.004	0.01	0.006	-0.003	0.005
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Census Block Group	0.005	0.011	0.041	0.013	-0.014	0.012
	(0.006)	(0.007)	(0.016)	(0.006)	(0.007)	(0.01)
No BG Controls	0.055	0.033	0.085	0.067	0.035	0.085
	(0.004)	(0.003)	(0.009)	(0.004)	(0.003)	(0.009)

	Current effects: 2016-2020					
	DV: Democratic Registration			DV: Republican Registration		
Treatment	Democrats	Republicans	Non-Partisans	Democrats	Republicans	Non-Partisans
Main	0.093	0.073	0.176	0.1	0.07	0.112
	(0.005)	(0.006)	(0.011)	(0.005)	(0.007)	(0.01)
Pre-trend	0.143	0.113	0.246	0.157	0.145	0.12
	(0.01)	(0.007)	(0.015)	(0.006)	(0.016)	(0.01)
Aspatial	0.05	0.035	0.077	0.053	0.039	0.05
	(0.007)	(0.006)	(0.013)	(0.005)	(0.007)	(0.008)
Dem. Ratio	0.102	0.054	0.111	-0.079	-0.075	-0.087
	(0.005)	(0.005)	(0.008)	(0.004)	(0.007)	(0.008)
Include Same Household	0.187	0.098	0.217	0.191	0.091	0.151
	(0.009)	(0.008)	(0.013)	(0.008)	(0.007)	(0.012)
100 Neighbors	0.058	0.045	0.112	0.064	0.047	0.076
	(0.003)	(0.004)	(0.006)	(0.003)	(0.005)	(0.007)
500 Neighbors	0.081	0.063	0.154	0.088	0.062	0.1
	(0.004)	(0.005)	(0.009)	(0.004)	(0.006)	(0.009)
Mile Radius	0.089	0.065	0.166	0.093	0.061	0.102
	(0.005)	(0.006)	(0.011)	(0.005)	(0.007)	(0.01)
New Neighbors	0.01	0.017	0.03	0.006	0.015	0.029
	(0.004)	(0.005)	(0.013)	(0.006)	(0.006)	(0.011)
Census Block	0.016	0.006	0.025	0.018	0.002	0.015
	(0.002)	(0.002)	(0.005)	(0.002)	(0.002)	(0.003)
Census Block Group	0.028	0.026	0.063	0.039	0.01	0.021
	(0.01)	(0.009)	(0.017)	(0.006)	(0.011)	(0.01)
No Census controls	0.09	0.073	0.175	0.099	0.07	0.114
	(0.005)	(0.006)	(0.01)	(0.004)	(0.007)	(0.01)
Race Posteriors	0.1	0.083	0.182	0.105	0.081	0.122
	(0.005)	(0.008)	(0.012)	(0.005)	(0.01)	(0.013)

Table S13: Alternative Treatment Estimates – downstream effects

	Downstream effects: 2012-2016 exposure change on 2016-2020 party switching					
	DV: Democratic Registration			DV: Republican Registration		
Treatment	Democrats	Republicans	Non-Partisans	Democrats	Republicans	Non-Partisans
Main	0.052	0.034	0.066	0.052	0.036	0.051
	(0.004)	(0.005)	(0.01)	(0.004)	(0.005)	(0.009)
Pretrend	0.129	0.07	0.131	0.134	0.076	0.081
	(0.012)	(0.007)	(0.018)	(0.012)	(0.009)	(0.008)
Aspatial	0.048	0.014	0.055	0.044	0.023	0.023
	(0.01)	(0.007)	(0.019)	(0.009)	(0.011)	(0.015)
Dem. Ratio	0.058	0.027	0.054	-0.044	-0.037	-0.045
	(0.004)	(0.004)	(0.01)	(0.003)	(0.005)	(0.006)
Include Same Household	0.057	0.033	0.07	0.054	0.031	0.052
	(0.004)	(0.004)	(0.01)	(0.004)	(0.004)	(0.008)
100 Neighbors	0.032	0.022	0.041	0.033	0.024	0.03
	(0.003)	(0.003)	(0.006)	(0.003)	(0.003)	(0.005)
500 Neighbors	0.046	0.03	0.06	0.044	0.032	0.045
	(0.003)	(0.005)	(0.009)	(0.003)	(0.005)	(0.007)
Mile Radius	0.05	0.03	0.062	0.047	0.031	0.043
	(0.004)	(0.004)	(0.009)	(0.004)	(0.005)	(0.008)
New Neighbors	0.03	0.003	0.035	0.025	0.025	0.022
	(0.008)	(0.007)	(0.016)	(0.01)	(0.009)	(0.014)
Census Block	0.015	0.006	0.011	0.015	0.003	0.01
	(0.003)	(0.002)	(0.005)	(0.003)	(0.003)	(0.006)
Census Block Group	0.036	0.011	0.043	0.029	0.023	0.035
	(0.009)	(0.011)	(0.019)	(0.01)	(0.012)	(0.017)
No Census controls	0.052	0.034	0.064	0.051	0.036	0.052
	(0.004)	(0.005)	(0.009)	(0.004)	(0.005)	(0.009)

6.6 Alternative approaches to downstream effects estimation

The main analyses estimate downstream effects on the subset of voters that do not change their party during the treatment period, estimating how changes in exposure during that period lead to party switching in the following four year period. This approaches offers the most straightforward comparison, separating party switching during the treatment period from party switching in the outcome period. In Figure S11, I present the main results side-by-side with two alternative estimations. The first subsets the data only by party in the first year of the treatment period. The second subsets by party in the first year and defines the outcome as party changes between the first year of the treatment period and the election 8 years later (so the effect of, say 2012-2016 party exposure changes on 2012-2020 party switching). As the figure shows, the choice of how to subset the results has little effect on the estimates, while redefining the outcome (in such a way where it now encompasses contemporaneous and downstream changes in party) produces larger estimates.

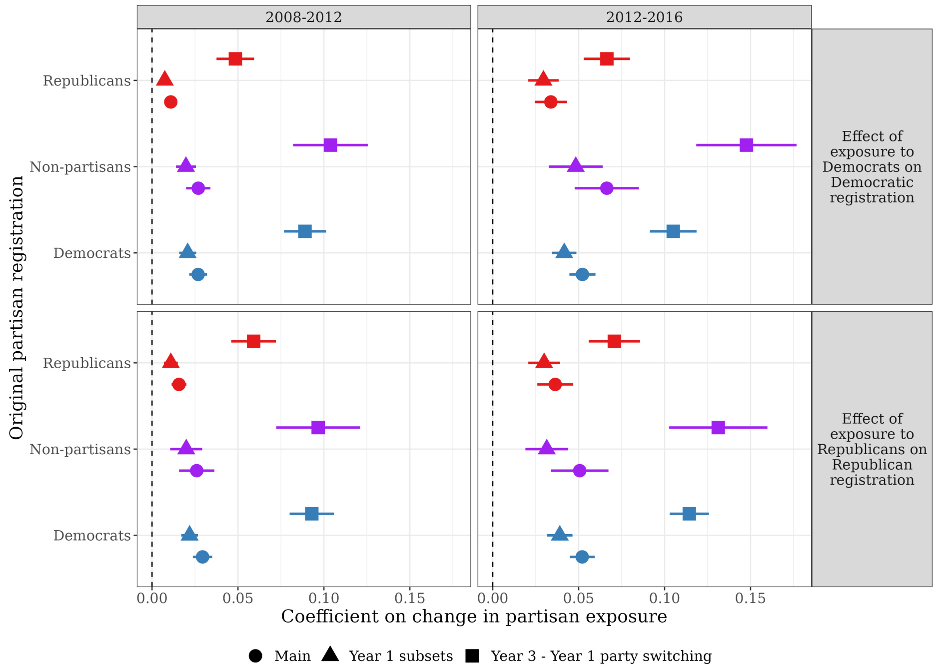


Figure S11: Downstream effects – alternative estimation strategies

7 Survey

7.1 Administering the Survey

The analyses in the main paper include data from an original survey. This survey is approved by the Institutional Review Board at Harvard University, the author's graduate school institution. This survey is part of a larger project designed to connect political attitudes to political geography - run in collaboration with other researchers at Harvard University. The survey was administered via email using email lists that had been linked to voter records. Since the emails were linked to voter records, the researchers could collect responses that could then be connected to respondent's exact residential location, allowing for analysis of how local geography (such as the partisan exposure metrics used in this analysis) corresponds with political attitudes. Previous research (see Brown and Enos (2021) and Block et al. (2021)) has used similar email lists for research purposes.

The email lists were provided by TargetSmart, and linked to voter data by the vendor. In total TargetSmart provided 72,506,065 emails, covering approximately 35% of nationwide registered voters. These data were stored on the graduate school institution's servers along with the voter data. Initially, we drew 7,315,500 emails at random from the lists. This was a nationwide sample, with an over-sample (1/3 of the sample) in the 5 states (California, Florida, Kansas, New York, and North Carolina) that were the focus of the study in this paper.

The survey was in the field from June 29, 2020 to August 28, 2020. The survey was taken online through Qualtrics. Surveys were delivered by e-mail via Qualtrics servers. Weekly sending limits were negotiated with Qualtrics through the author's graduate school institution, and have varied over time. Each sampled email address was sent an initial invitation email. However, of the emails drawn from the TargetSmart lists, 2,687,661 proved undeliverable – a bounce rate of 36.7%. Emails were undeliverable either because the email was invalid or the email invitation was rejected by recipients' servers. In total, 4,826,036 voters were successfully contacted. This number is a generous estimate of how many voters saw the email in their inbox because we probably do not observe some bounced emails and many emails may end up in junk mail. These 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.

This survey administration yielded a total of 71,505 responses for a response rate of 1.48%. Of these responses, 92.2% verified that they were the person listed in the voter data. 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 24,433 voters.

Participation in the survey was voluntary. Some people who were contacted reached out to the researchers to confirm if the survey was real. In these cases we responded confirming the legitimacy of the survey but did not explain the research purposes beyond the information already included in the invitation email and the consent forms. Participants were not compensated for participation in the survey and were aware they were taking part in a research study. Compensation was not offered 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.

7.2 Survey Weights and Descriptive Statistics

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 S14 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 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

Table S14: Survey Descriptive Statistics and Population Comparisons

	Registered Population	Sample	Sample Weighted
Democrat	0.424	0.411	0.379
Married	0.370	0.537	0.415
Republican	0.271	0.366	0.281
White	0.641	0.856	0.630
Black	0.103	0.051	0.096
Hispanic	0.165	0.052	0.178
Asian	0.050	0.018	0.055
Female	0.511	0.513	0.508
Age	50.097	62.090	54.118
Democratic Exposure	0.433	0.380	0.420
Republican Exposure	0.264	0.317	0.276
Block Group White	0.543	0.668	0.564
Block Group Registered	0.481	0.626	0.587
Block Group Median Age	41.294	43.763	41.263
Block Group Median Household Income	78, 956.678	84, 405.278	80, 222.680
Block Group Homeowner	0.629	0.712	0.657
Block Group Median Year House Built	1, 974.427	1, 978.039	1, 973.072
Block Group Drive to Work	0.810	0.849	0.829
Block Group Median House Value	421, 767.163	404, 258.340	404, 407.875
Vote 2016 General	0.662	0.951	0.618
Vote 2018 General	0.576	0.912	0.521

the averages of the broader population.

7.3 Survey Results

7.4 Relationship between comfort with neighbors knowing party and party switching

Here I present analyses that measuring the relationship with comfort with the idea of one's neighbors knowing their party and party switching. The general expectation is that voters who are less comfortable with the idea of their neighbors knowing their party will be more likely to switch their party. To test this, I create subsets of the survey data based on whether a respondent was a Democrat, Republican, or non-partisan in 2016. Separately for

Table S15: Full survey results – Perception of neighbors' party, contact with partisan neighbors, and comfort with neighbors' knowing partisanship

	Neighbors: Democrats or Republicans				Contact: Democrats		Contact: Republicans		Comfort: Neighbors know Party			
	(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
Weights	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
R2	0.600	0.507	0.599	0.507	0.407	0.268	0.469	0.323	0.440	0.261	0.444	0.266
R2 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

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

each subset, I predict whether the respondent was a Democrat or Republican in 2020 as a function of their response to the comfort question. I control for individual characteristics from the main survey specification, but do not include aggregate controls such as partsian exposure or Block Group variables. I do include Zip Code fixed effects. Since the quantity of interest is the predictive effect of individual-level comfort on party switching, standard errors in these models are clustered at the individual level. All models use survey weights. I estimate the following models

$$D_i = \theta Comfort_i + \boldsymbol{\beta X}_i + \gamma_z + \epsilon_i \tag{1}$$

$$R_i = \theta Comfort_i + \boldsymbol{\beta X}_i + \gamma_z + \epsilon_i \tag{2}$$

where the quantity of interest θ is the predictive effect of comfort on whether a respondent is a Democrat (D_i) or Republican (R_i) in 2020. The expectation is that comfort should be positively correlated with being a Democrat in 2020 for respondents who were Democrats in 2016 (comfortable Democrats are likely to remain Democrats, while uncomfortable ones may defect), and negatively correlated for those that were Republicans or non-partisan in 2016 (i.e. uncomfortable Republicans are more likely to defect to the Democratic party). Similarly, comfort should be positively correlated with being a Republican in 2020 for respondents who were Republicans in 2016, and negatively correlated for those that were Democrats or non-partisan in 2016.

Since the survey is one-off cross-sectional survey, this is a limited test of whether discomfort leads to party switching. I do not have measures of how comfortable a respondent felt with the idea of their neighbors knowing their party in 2016, only in 2020. Therefore, it cannot be determined from these data whether measured comfort is reflective of conditions prior to a party switch, or whether party switching itself causes a change in levels of comfort. This makes it difficult to test whether discomfort leads to party switching, since a voter that switches parties due to discomfort may become more comfortable after switching, and thus report in the survey a higher level of comfort than they would have if surveyed in 2016. Therefore, these results should be interpreted with caution.

Table S16 reports the coefficients from the models. The coefficient for Democrats in model 1 is positive and significant, indicating that 2016 Democrats who report higher levels of comfort were more likely to remain Democrats in 2020. The coefficient for Republicans in model 2 is negative, indicating that 2016 Republicans who were more comfortable were less likely to change parties – but that those that were less comfortable were more likely to become Democrats. The coefficient for non-partisans in model 3 is not significant at conventional threshholds. For models 4-6 which predict 2020 Republican partisanship, the comfort coefficient for Democrats is negative but not significant, while the coefficient for Republicans is positive and significant, in line with expectations. The coefficient for non-partisans is again not significant. Table S17 reports the results without survey weights which are generally similar to the results with weights.

8 Robustness of results to alternative sample construction

8.1 Alternative sample construction strategy

The main analysis in this paper relies on TargetSmart's data cleaning procedures, using each voter record where, by their standards, they have identified the most up to date record for a unique voter. However, data vendors may be conservative in their data purging practices, and deadweight or duplicated records in the voter data may bias results. To test how such measurement challenges may influence the takeaways from this paper, I replicate the main

Table S16: Predicting party switching by comfort with neighbors knowing party

	DV: 2020 Democrat			DV: 2020 Republican		
	2016 Democrats (1)	2016 Republicans (2)	2016 Non-partisans (3)	2016 Democrats (4)	2016 Republicans (5)	2016 Non-partisans (6)
Comfort	0.008*	-0.007+	0.007	-0.002	0.009*	0.007
	(0.004)	(0.003)	(0.007)	(0.003)	(0.004)	(0.007)
Asian	0.056+	0.100	0.036	-0.021	-0.079	0.021
	(0.032)	(0.081)	(0.036)	(0.018)	(0.085)	(0.039)
Black	0.031	0.048	-0.026	-0.019	-0.043	0.032
	(0.024)	(0.051)	(0.035)	(0.016)	(0.058)	(0.026)
Hispanic	0.021	0.041	0.021	-0.002	-0.052+	-0.011
	(0.026)	(0.028)	(0.033)	(0.017)	(0.031)	(0.029)
White	0.008	0.013	0.037	0.008	-0.018	0.023
	(0.022)	(0.026)	(0.027)	(0.014)	(0.028)	(0.019)
Age	0.001+	0.000	0.000	0.000+	0.000	-0.001
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Male	-0.010	-0.014*	-0.026+	0.003	0.008	-0.037+
	(0.009)	(0.007)	(0.014)	(0.006)	(0.009)	(0.019)
Married	-0.019+	-0.013+	-0.010	0.005	0.015+	0.020
	(0.010)	(0.007)	(0.015)	(0.006)	(0.009)	(0.016)
College	0.016+	0.017*	0.017	-0.006	-0.011	-0.021
	(0.008)	(0.007)	(0.014)	(0.006)	(0.009)	(0.020)
Years Residence	-0.001*	0.000+	0.000	0.000*	0.000	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Num.Obs.	6,535	5,695	3,636	6,535	5,695	3,636
R2	0.614	0.618	0.709	0.575	0.637	0.765
R2 Adj.	0.371	0.359	0.398	0.307	0.391	0.514

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table S17: Predicting party switching by comfort with neighbors knowing party - no survey weights

	DV: 2020 Democrat			DV: 2020 Republican		
	2016 Democrats (1)	2016 Republicans (2)	2016 Non-partisans (3)	2016 Democrats (4)	2016 Republicans (5)	2016 Non-partisans (6)
Comfort	0.003	-0.005+	0.002	-0.001	0.010**	0.006
	(0.003)	(0.003)	(0.006)	(0.002)	(0.004)	(0.004)
Asian	0.033	0.016	0.014	-0.013	0.005	-0.012
	(0.024)	(0.027)	(0.046)	(0.016)	(0.032)	(0.032)
Black	0.042*	0.054	-0.021	-0.025+	-0.043	0.021
	(0.019)	(0.056)	(0.030)	(0.013)	(0.066)	(0.032)
Hispanic	0.021	0.020	0.015	-0.001	-0.028	0.009
	(0.020)	(0.021)	(0.033)	(0.013)	(0.025)	(0.024)
White	-0.004	-0.011	0.033	0.014	0.009	0.014
	(0.017)	(0.015)	(0.023)	(0.012)	(0.019)	(0.020)
Age	0.001**	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Male	-0.009	-0.016**	-0.025*	0.000	0.008	-0.021*
	(0.007)	(0.006)	(0.013)	(0.005)	(0.008)	(0.009)
Married	-0.006	-0.016*	-0.016	0.000	0.023**	0.008
	(0.007)	(0.006)	(0.013)	(0.005)	(0.009)	(0.009)
College	0.027**	0.018**	0.017	-0.019**	-0.012	-0.022+
	(0.009)	(0.006)	(0.013)	(0.007)	(0.008)	(0.012)
Years Residence	0.000*	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Num.Obs.	6,535	5,695	3,636	6,535	5,695	3,636
R2	0.464	0.454	0.603	0.467	0.459	0.630
R2 Adj.	0.128	0.085	0.180	0.132	0.094	0.237

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

results in the manuscript using a sample of TargetSmart records that builds on TargetSmart's initial linkage work to more aggressively remove potential deadweight from the sample. The cleaning process takes place on the entire nationwide sample of TargetSmart data from 2012-2021, not just the states and years in this analysis. After running this alternative cleaning process I then subset to the states and years that are the focus of this paper's analysis.

This cleaning pipeline was developed in collaboration with Brown et al. (2023)[4], and is part of a larger project to identify movers in the voter data. Identifying movers requires more aggressive de-duplication. Thus, this sample construction strategy is designed to give greater weight to removing false positives (removing out-of-date records), than to avoiding false negative errors (removing actual voters from the data). The sample construction in the main analysis is a more conservative approach, prioritizing keeping records over removing them. But replicating the results on both samples allows for assessment of the sensitivity of the results to these measurement challenges with voter data.

TargetSmart provides a "voterbase ID" field (henceforth VBID) that uniquely identifies each row for a given state and year. TargetSmart also provides an "exact track ID" (henceforth ETID), which represents TargetSmart's efforts to link individuals *across* years and states. We use this information plus first name, middle name, last name, date of birth, and vote history to de-duplicate the TargetSmart data. We also use this information to expand on TargetSmart's linkage model to further link voters across states and years.

The details of this process are described below. First, we take the following steps to clean the raw TargetSmart files:

1. Use TargetSmart's field on whether a voter is found in the Social Security Death records to drop voters that are deceased.

2. Use TargetSmart's information from the United States Postal Service National Change

[4]Much of the details in this SI describing this alternative cleaning strategy are reproduced from Brown et al. (2023). See https://www.nber.org/papers/w31759.

of Address database to drop voters that no longer reside at their listed residence.

3. Remove hyphens and spaces from first and last names. Capitalize all letters of first and last names.

4. Recode invalid ZIP Codes and census block group IDs as missing.

5. De-duplicate records with the same ETID, first name, and last name, giving preference to the record whose registration status is "Registered" (vs. "Unregistered"), voter status is "Active" (vs. "Inactive," based on recent election participation), and with the most recent registration date.

6. Drop any records where the voter's age is listed as under 18 and the individual is listed as "Registered."

To link rows *within the same state* corresponding to the same individual but across multiple years – in other words, to assign a state unique identifier (henceforth "SUID") – we take the following steps:

1. Split the DOB field into year, month, and day. Due to unreasonable high frequencies of DOBs ending in `01` and `0101`, in case the DOB ends in `01`, set the DOB day to missing. If the DOB ends in `0101`, set the DOB month and day to missing.[5]

2. Assume records that share a VBID are the same person, and assign them the same SUID. But if the same VBID has been assigned to two rows where the first name, last name, and date of birth are *all* different, or where the maximum difference in birth year is more than 5 years *and* the month and day of birth are different too, then break this link.

[5]We lose information by including some people who were actually born on the first of the month, or who were actually born on January 1. However, there is no reliable way of determining whether a DOB ending in `0101` actually corresponds to a January 1 birthday, or whether it indicates that the month and day are missing.

3. Group by ETID.

    - Case 1: If *at least one* of the first name, last name, and DOB are the same among all members of the group, and there's only one record per year, and the maximum age difference is less than or equal to five years, then assign all rows the same SUID.
    - Case 2: If not everyone in the group shares *either* a first name, last name, or DOB, group them by name and DOB and – as long as there is only one record per year – assign rows within each group the same SUID.

4. Group by first four letters of first name, last name, year of birth, and address. Ensure that:

    - Each record has non-missing information for all of the grouping variables.
    - Each record is unique *within a year* by these variables.

    If so, assign these rows the same SUID.

5. Repeat the previous step using the following sets of grouping variables:[6]

    - First name, last name, year of birth, and address.[7]
    - First name, last name, and date of birth.
    - First name, last name, and year and month of birth.
    - First name, last name, and year of birth.
    - First name, middle name, last name, and date of birth.

[6] If month and day of birth are not in the set of grouping variables, we ensure that when non-missing, they do not conflict. We also ensure that middle initials, when non-missing, do not conflict, *except* if the set of grouping variables includes address and year of birth, or includes exact date of birth.

[7] We only de-duplicate records if no more than 15 people ever lived at the same address, and if the difference between the maximum and minimum year of birth is no more than 5 years.

- First name, middle name, last name, and year and month of birth.
- First name, middle name, last name, and year of birth.

8.2 De-duplicating across states

To link rows corresponding to the same individual *across* states – in other words, to assign a nationally unique identifier (henceforth "UID") – we take the following steps.

1. Drop rows missing first name, last name, or DOB.
2. As above, if the DOB ends in `01`, set the DOB day to missing. If the DOB ends in `0101`, set the DOB month and day to missing.
3. Group by ETID and check that the maximum vote count for any election is one. If so, assign these rows the same UID.
4. Group by first name, last name, and date of birth. Ensure that:
   - Each record has non-missing information for all of the grouping variables.
   - Each record is unique by these variables within state.
   - The group has a record from at least two states.
   - The maximum vote count among records in the group for any election is one.

   If so, assign these rows the same UID.
5. Repeat the previous step using the following sets of grouping variables:[8]
   - First name, last name, and year and month of birth.
   - First name, middle name, last name, and year, month, and day of birth.

[8] As above, if month and day of birth are not in the set of grouping variables, we ensure that when non-missing, they do not conflict. We also ensure that middle initials, when non-missing, do not conflict, *except* if the set of grouping variables includes exact date of birth.

- First name, last name, and year of birth.
- First name, middle name, last name, and year and month of birth.
- First name, middle name, last name, and year of birth.

8.3 Descriptive statistics of alternative sample

With the output from this alternative sample construction, I re-calculate for each voter their 1,000 nearest registered neighbors and from that reconstruct their partisan exposure metrics. After subsetting to voters that do not move across presidential election cycles, I am left with 36,158,092 unique voter records across the 2008-2012, 2012-2016, and 2016-2020 periods of study. Table S18 shows the sample sizes in these alternative samples compared to the samples in the manuscript. In general, this alternative cleaning process reduces the sample sizes by approximately 12%-15%.

Table S18: Comparing sample sizes between main and alternative samples

	Registered Voters		
Sample	Main	Alternative	%
2008-2012	17,391,433	16,672,706	95.87%
2012-2016	22,565,114	19,662,423	87.14%
2016-2020	29,327,029	24,820,184	84.63%
Unique voters (across samples)	41,090,037	36,158,092	88.00%

Figure S12 shows the partisan transition matrix for this sample, while Figure S13 shows the distribution of changes in partisan exposure. I also report in Table S19 the correlation across samples in the changes and levels of partisan exposure across both samples. The correlations for levels (partisan exposure at any given snapshot in time) are between 0.98 and 0.99, while the correlations for differences are between 0.89 and 0.93.

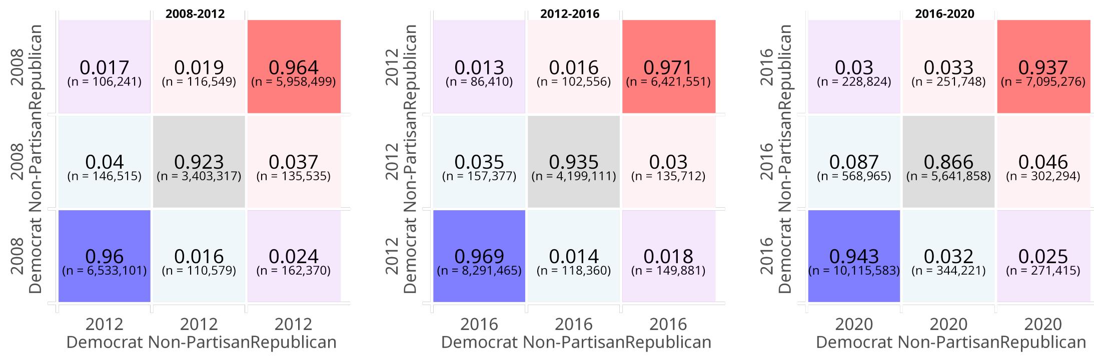


Figure S12: Partisan Transition Matrices – alternative sample

Tiles show the proportion of Democrats, Republicans, and Non-Partisans in year 1 of each panel who were registered to each political party in year 2 for the 2008-2012, 2012-2016, and 2016-2020 panels.

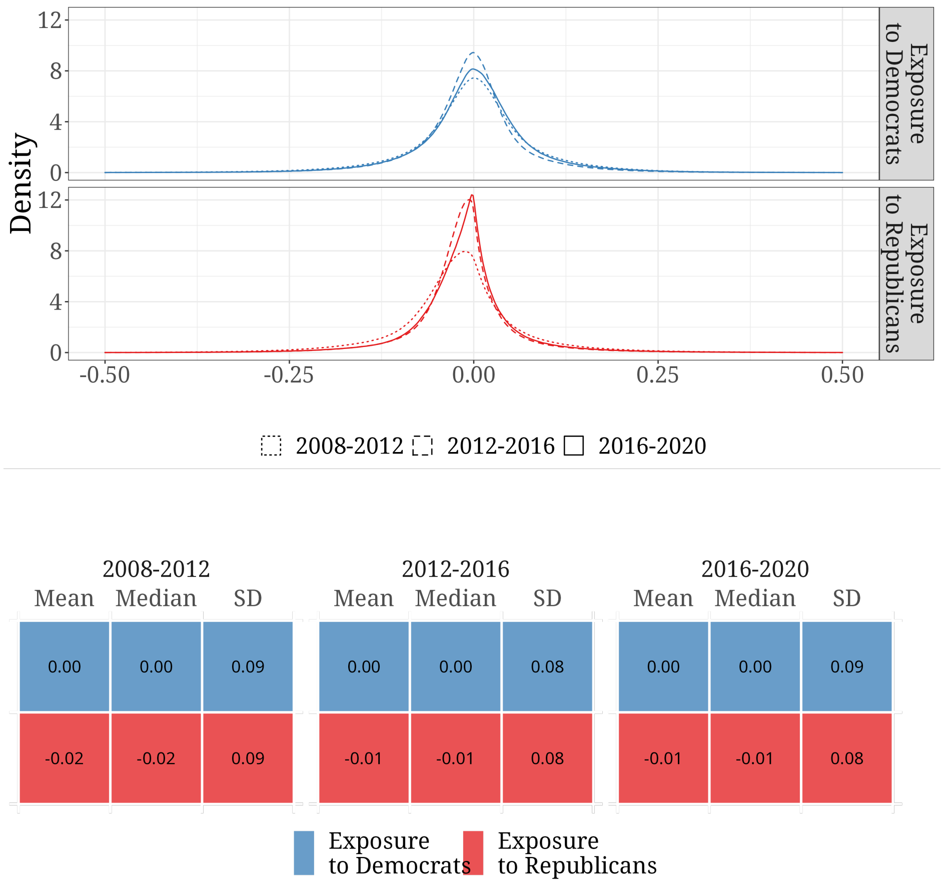


Figure S13: Distribution of Changes in Democratic and Republican Exposure – alternative sample

Figure plots the distribution of changes in Democratic (blue) and Republican (red) exposure across time for voters in the 2008-2012 (solid lines), 2012-2016 (dashed), and 2016-2020 (dotted) linked samples. Table presents the mean, median, and standard deviation of these distributions.

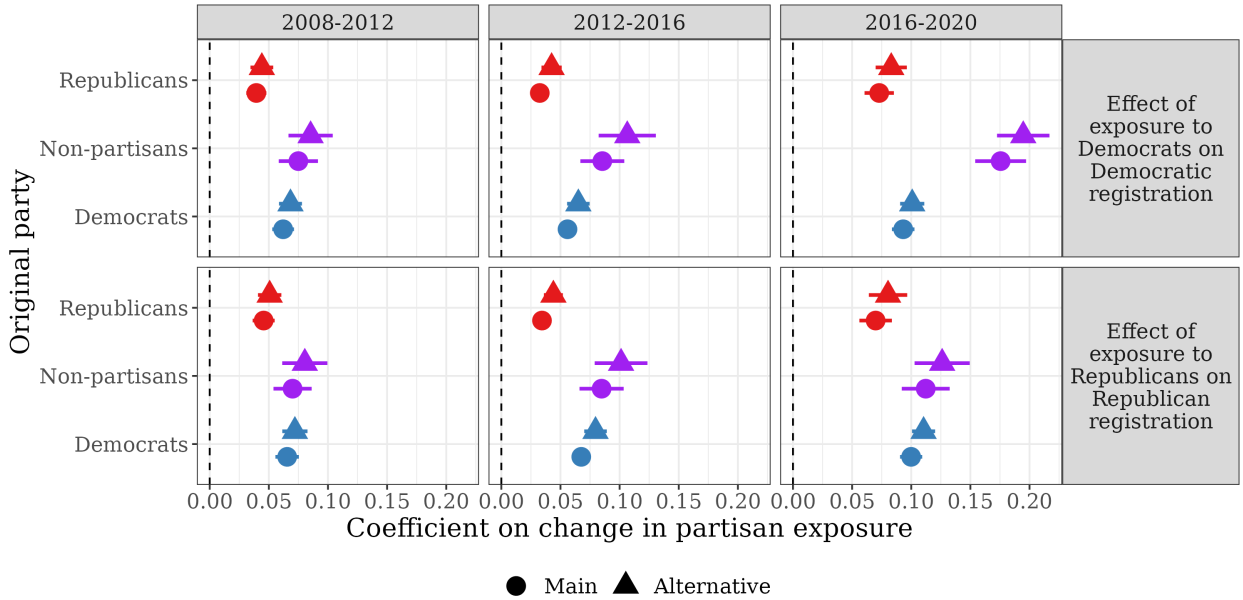
Table S19: Correlation between individual-level partisan exposure across main and alternative samples

Sample	Exposure	Stat	Correlation
2008-2012	Democrat	2012	0.98
2008-2012	Democrat	Δ 2008-2012	0.93
2012-2016	Democrat	2012	0.98
2012-2016	Democrat	2016	0.98
2012-2016	Democrat	Δ 2012-2016	0.89
2016-2020	Democrat	2016	0.98
2016-2020	Democrat	2020	0.99
2016-2020	Democrat	Δ 2016-2020	0.90
2008-2012	Republican	2012	0.98
2008-2012	Republican	Δ 2008-2012	0.93
2012-2016	Republican	2012	0.98
2012-2016	Republican	2016	0.98
2012-2016	Republican	Δ 2012-2016	0.89
2016-2020	Republican	2016	0.98
2016-2020	Republican	2020	0.98
2016-2020	Republican	Δ 2016-2020	0.89

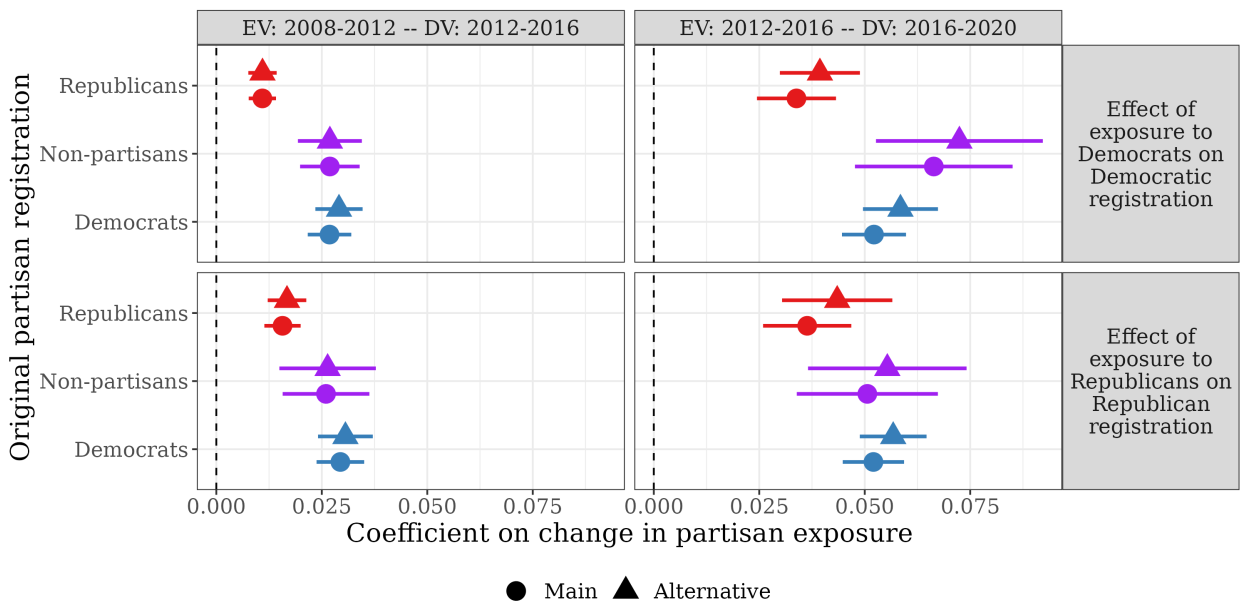
Table reports correlations between individual-level measures of partisan exposure across the main and alternative samples. For each sample, correlations for both levels and differences are reported. The 2008 levels correlation is not reported because the alternative sample construction was only done for TargetSmart voter files, which cover 2012 and later.

8.4 Results

With this alternative sample, I reproduce the main estimates from the manuscript. FigureS14 plots the coefficients from the alternative sample side-by-side. Across current and downstream effects, results from this alternative sample are very similar to those in the manuscript. The point estimates from the alternative sample are usually slightly larger, but are for the most part not statistically distinguishable from the estimates in the main analysis.



(a) Current effects



(b) Downstream effects

Figure S14: Effects of Partisan Exposure on Partisan Registration

Figure plots effect of a one unit increase in Democratic exposure on Democratic partisanship (top row) and the effect of a similar increase in Republican exposure on Republican partisanship (bottom row). Panel (a) is the current effects – the effect of changes in partisan exposure on party switching during the same time period. Panel (b) is the downstream effects – the effect of changes in partisan exposure on party switching in the following 4-year period. Results are plotted separately for subsets based on partisanship in the first year of the linked sample. Circular points plot coefficients from the main analysis sample, while triangles plot the effects from the alternative sample. Bars plot 95% confidence intervals.

Table S20: Survey results – alternative sample

	Neighbors: Democrats or Republicans				Contact: Democrats		Contact: Republicans		Comfort: Neighbors know Party			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dem Exp	1.166***	1.154***			0.934**	0.710***			-0.051	-0.087		
	(0.148)	(0.106)			(0.328)	(0.196)			(0.288)	(0.150)		
Dem Exp * Dem									0.327	0.512*		
									(0.309)	(0.207)		
Rep Exp			-1.344***	-1.347***			1.917***	1.832***			-0.209	-0.405*
			(0.140)	(0.120)			(0.314)	(0.187)			(0.244)	(0.167)
Rep Exp * Rep											0.830**	1.139***
											(0.310)	(0.194)
Num.Obs.	17,324	17,324	17,324	17,324	16,444	16,444	16,467	16,467	13,008	13,008	13,008	13,008
R2	0.626	0.526	0.626	0.528	0.425	0.285	0.487	0.335	0.451	0.279	0.454	0.283
R2 Adj.	0.533	0.409	0.534	0.411	0.276	0.100	0.354	0.162	0.272	0.043	0.276	0.049
Weighted	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This consistency should strengthen confidence in the results. The results are very similar across sample construction strategies, so both conservative and more aggressive approaches to data processing produce the same statistical results and substantive conclusions. Thus, any bias from deadweight voter records in the data is likely small. If anything, since the the alternative sample results, to the extent they differ at all, are slightly larger than those from the main sample, then the results indicate that such bias attenuates the effect estimates.

Table S20 reports the coefficients from the survey results using this alternative sample. Again, the coefficients are very similar to the survey results in the main analyses, and the survey results still support the conclusions that local partisan exposure is predicts how voters perceive the partisanship of their neighbors, their contact with partisan neighbors, and whether they are comfortable expressing their partisanship around their neighbors.

References

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