Partisan Conversion Through Neighborhood Influence: How Voters Adopt the Partisanship of their Neighbors and Reinforce Geographic Polarization

January 7, 2022

Abstract

Recent studies show that American neighborhoods have become politically homogeneous, raising concerns about how geographic polarization divides parties and influences voters. I argue that one consequence (and cause) of homogeneity is that voters are influenced to adopt the partisanship of people they live near. Panel data on over 41 million voters from 2008-2020 and an original survey of 24,623 respondents demonstrate that exposure to partisans increases the likelihood of switching registration to match local partisanship. Effects are largest for voters most likely to interact with neighbors: older voters, voters in single-family communities, and voters with more same-race neighbors. Moreover, survey data show that voters accurately perceive local partisanship, interact more with partisans they live near, and view Democrats or Republicans more favorably when they have more neighbors from that party. Partisanship is thus shaped by where voters live, and this conversion reinforces ongoing political segregation.

Introduction

In the United States, Democrats and Republicans increasingly live around neighbors who share their political preferences and partisan attachments (Sussell, 2013; Brown and Enos, 2021; Kaplan, Spenkuch, and Sullivan, 2022). This local homogeneity creates electoral imbalances that threaten fair representation (Chen and Rodden, 2013; Eubank and Rodden, 2020), erodes support for regional policies such as transit and infrastructure (Nall, 2018; Trounstine, 2018), and provokes concerns that living in isolated communities exacerbates differences between polarized parties (Cramer, 2016). Given these trends, it is important to understand what is causing geographic homogeneity, and how partisan neighborhoods influence voters.

Most of geographic polarization is due to sorting by characteristics associated with politics, such as race or class (Rodden, 2019), and the alignment of partisanship with these geographically concentrated demographics (Levendusky, 2009). In addition, there are two channels through which politics may directly influence partisan sorting. First, through *separation* – voters choosing to live around politically like-minded neighbors – neighborhoods may increasingly become Democratic or Republican. However, voters do not seem to choose where to live based on local partisanship (Mummolo and Nall, 2017), and partisan bias in residential mobility is too small to account for increases in geographic polarization (Martin and Webster, 2018). This points to an overlooked source of homogeneity, *conversion*, where voters adopt the partisanship of those they live near.

In this study, I argue that voters are influenced by local partisanship, and this residential exposure produces partisan conversion that reinforces local homogenization. As neighborhoods become Democratic or Republican, voters take in information about changing partisan norms, interact with partisan neighbors, and feel social pressure to conform or may derive internal utility from political commonality with their local community (Gerber, Green, and

Larimer, 2008; Klar, 2014). As a result, voters with malleable partisan attachments who see increases in exposure to Democrats or Republicans will be influenced to change their partisan registration to match. For voters whose registration already matches local trends, co-partisan neighbors will make it more likely that they remain with that party.

While there is limited prior evidence linking local context to partisanship, experimental and observational research demonstrates that voters are influenced by local norms when making political donations (Perez-Truglia, 2017; Perez-Truglia and Cruces, 2017), voting (Green et al., 2016; Anoll, 2018), and other behaviors such as littering, church attendance, criminal activity, school enrollment, employment, and drug and alcohol use (Cialdini, Reno, and Kallgren, 1990; Case and Katz, 1991; Bobonis and Finan, 2009). Recent research demonstrates that moving to a new state or county influences voter registration (Cantoni and Pons, 2021), and other dimensions of geography such as race and class powerfully influence attitudes and behavior (Putnam, 2007; Enos, 2017; Sands, 2017). As neighborhoods become politically homogeneous, through a combination of new neighbors moving into the community, new voters entering the electorate, and changes in partisanship, do these neighborhood changes make voters more likely to change their partisan affiliations? And to what extent are political changes specifically – rather than other dimensions of context – influencing voters?

Tests of geographic influence on political behavior face persistent measurement and design challenges. Precise data on where voters live in relation to each other are scarce, and most exposure measures rely on aggregate demographics. Furthermore, such analyses are prone to issues of sorting and endogeneity, and researchers often lack exogeneous leverage on geographic variables or over-time data with sufficient power to make credible causal comparisons. With these challenges in mind, I construct a panel of over 41 million voters drawn from linked administrative registration records from California, Florida, Kansas, New York, and North Carolina, spanning 2008-2020. These data document nearly every registrant in these states during the time period, recording for each year voters' residential addresses and partisan registrations. I supplement these data with an original survey of 24,623 voters from the panel.

With these data, I conduct two analyses. First, I measure the effect of exposure to Democratic and Republican neighbors on partisan registration. For identification, I focus on voters who do not change residences between elections but see their neighborhoods change around them, and use an estimation strategy that compares voters matched on starting partisanship, race, age, marital status, Zip Code, and starting levels of partisan exposure but who see different over-time changes in exposure to Democrats and Republicans among their closest neighbors. This comparison allows better attribution of changes in registration to changes in partisan exposure, and I also estimate alternative specifications that match on pre-trends in the treatment and outcome to further support these causal inferences.

Second, with the survey data I measure whether voters are aware of neighbors' partisanship, and the relationship between partisan exposure and interaction with partisan neighbors, comfort with neighbors knowing one's partisanship, perceptions of the party ideology, and feelings of warmth towards Democrats and Republicans. These analyses test whether voters are responsive to the political norms of their local environment and illustrate how these norms influence partisan attitudes and registration.

The data show that increased residential exposure to Democrats or Republicans makes voters more likely to switch registration to match local partisanship. A one standard deviation ($\sim$ 10 percentage points) increase in exposure to Democrats or Republicans between presidential elections increases the likelihood of switching to that party by 1-3 percentage points. Since just 5.7% of voters change their party registration between presidential elections, these effects constitute a 20%-60% increase over baseline probabilities of changing party.

These effects are largest for voters most likely to interact with and be influenced by their neighbors: older voters, voters in single-family communities, and voters who see increased partisan exposure from neighbors who are the same race as them. The survey data further show that voters accurately report neighbors' partisanship, interact more with Democrats and Republicans when they live close to them, are more comfortable expressing their partisanship when it matches their neighbors', and hold more positive perceptions of neighbors' political parties.

Overall, the results indicate that voters' registration and partisan attitudes are responsive to changes in the partisan composition of their residential communities. While for many voters partisanship is stable and likely pre-dominantly determined by early-life socialization (Campbell et al., 1960), shifts in partisan context prompt some voters to change registration. Political group membership is thus influenced by the membership of one's neighbors, demonstrating that an integral component of voter's political identity, the party to which they are registered, is in part determined by where voters live and who they live near.

These findings also suggest that contextual effects will reinforce geographic polarization. Partisan conversion is not the primary driver of geographic polarization, but simulation analysis shows that social influence can explain approximately 10% of the recent increase in partisan segregation. Therefore, as communities become politically homogeneous, some voters change their party to match, exacerbating political isolation and the (geographic) distance between parties.

Partisan Conversion through Neighborhood Influence

Partisanship is often characterized as a social identity (Green, Palmquist, and Schickler, 2004), but it is also malleable, sensitive to factors that affect the expression or suppression of political affiliations (Klar and Krupnikov, 2016). Changes in partisanship can result from changes in context that alter the balance of these influences (Berelson, Lazarsfeld, and McPhee, 1954). Family and friends tend to be the most powerful contexts that determine political attitudes, but other contexts may also have effects. These less direct contexts, such as neighborhoods, are more likely to shift in composition and thus may more readily influence changes in partisanship.

I argue that partisan geography provides a key context in which people are socialized into politics and norms of political expression are established and reinforced. Voters follow these norms, adopting the group membership and behaviors of those around them. As neighborhoods grow more Democratic or Republican, new perceptions of partisan norms alter the calculus of whether to conform. For voters with marginal partisan attachments, this process prompts reconsideration of their partisan affiliations.

Who voters live near structures who they come in contact with in their residential lives and the observed behaviors that voters may adopt or be socialized into.[1] Voters may infer partisan norms from direct cues such as conversations with neighbors, political yard signs or bumper stickers, local media, or targeted campaign messages, and from indirect cues such as neighbors' cars, jobs, whether they are religious, what products they buy, what music they listen to, or other lifestyle choices from which voters infer partisanship (Lee, 2021). Knowledge of descriptive norms creates perceptions of social pressure or rewards (Legros and Cislaghi, 2019) that may push voters to reconsider their partisan affiliations. This could be perceptions of community judgement for opposing beliefs or internal utility that comes from feeling similar to one's community.

This process does not require that voters have extensive relationships with neighbors. According to a 2018 Pew survey (Parker et al., 2018), 87% of adults know at least some of their neighbors, 31% report knowing most, and 44% say they communicate weekly with neighbors. For these voters the socializing influence of neighborhoods may flow through interpersonal contact. But neighborhoods can still exert influence on voters with limited

[1]Though the rise of social media may suggest a declining importance of geographic context, online connectivity actually enhances neighborhood connectivity, as people can more easily coordinate face-to-face interaction, and more easily find local businesses and events through social media (Goldenberg and Levy, 2009).

neighbor contact. Conversations with neighbors are just one of many informational cues from which voters infer partisan norms, so even voters who do not frequently interact with neighbors likely have an accurate sense of their partisanship, and still may respond to social pressure from descriptive norms.

Additionally, proximity can create affinity through shared ownership of space (Henderson, 2009) that may reframe how voters view partisans. When voters think of Democrats or Republicans they may think of stereotypes of hyper-partisans, potentially from images from national media (Ahler and Sood, 2018). But with more neighbors from a political party, new images may emerge for what it means to be Democratic or Republican, and voters may reconsider their own registration within this new frame.

Social Influence on Partisan Registration

Conversion in this model happens through changes in partisan registration. Registration is reflective of partisan preference and an important political outcome itself, structuring how politicians view constituents (Porter and Rogowski, 2018), how districts are drawn (Chen and Rodden, 2013), and how campaigns mobilize voters (Hersh, 2015). Registration also has downstream influence on partisan attitudes, strengthening ties to the party one is registered to (Gerber, Huber, and Washington, 2010), and shapes issue positions and political participation (Highton and Kam, 2011; Wray-Lake, Arruda, and Hopkins, 2019).

I anticipate that changes in partisan context produce changes in registration primarily by altering social pressures, norms, and strategic calculations that govern the translation of partisan preference into partisan affiliation. Preference change in response to exposure to new political ideas may also occur, but changing attitudes, and translating these attitudes into new partisan affiliations, is a slow process. In general, social pressure and norm adoption better explain changes in explicit behavior or group membership than attitude change (Druckman and Green, 2013). Shifts in partisan preferences mainly occur in response to long-term socialization or major policy shifts (Campbell et al., 1960).

When Should Social Influence be Strongest?

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).

Alternative Expectations

Alternative models offer competing predictions for how voters should respond to local partisanship. Some scholars point to the decline of neighborhoods as social institutions in day-to-day life (Putnam, 2001), suggesting that the influence of neighbors may be weaker than in the past (Abrams and Fiorina, 2012). Living in homogeneous partisan environments could also create collective action problems, where voters do not need to affiliate with their preferred party since the party is already likely to do well in their area (Olson, 1965). Additionally, the rise of independents has been attributed to growing disdain for partisan politics (Klar and Krupnikov, 2016), so an increase in partisan exposure may drive voters to de-affiliate.

Voterfile Data

Studies connecting political behavior to geography usually rely on aggregate summaries of geographic and behavioral variables, and are thus impeded by measurement error common to ecological inference (Openshaw, 1983). Causal inference in such analyses is also challenging, as absent temporal variation or natural population shocks researchers must make likely implausible identifying assumptions. With this in mind, I construct a panel of voters across 5 states covering 2008-2020, with even longer panels in some states. These data contain information on residential address and partisan registration for each year during which a voter was registered, and I use this information to measure exposure to Democrats and Republicans across time and connect changes in exposure to changes in registration.

I construct the panel using voterfiles from California, Florida, Kansas, North Carolina, and New York. These states offer varied regional and political contexts and encompass 27% of the U.S. electorate and 48% of voters living in states that record partisanship. All voter data from 2012-2020 were provided by the vendor Target Smart. Pre-2012 data were collected from states. Each file contains data on voter name, residential address, age, gender, partisan registration, vote history, and race. Race is recorded in Florida and North Carolina, and is imputed by Target Smart in the other states based on name and census demographics[2].

I analyze linked samples across 3 presidential electoral cycles: 2008-2012, 2012-2016, and 2016-2020. I rely on Target Smart's linkages for 2012-2020 data, and I link pre-2012 files to the Target Smart panel by matching on name, birth year, and residential address. I do not employ fuzzy string or probabilistic linking, instead adopting a conservative approach with exact matching to avoid false positives, which would inflate the rate of partisan switching.

[2]Racial imputation methods are commonly used in voterfile research and have been shown to be highly accurate (Imai and Khanna, 2016). In Supporting Information Section S6.3, I estimate alternative specifications using the posterior probability of being White from the imputation calculations. The results are consistent in these alternative estimations.

This results in 41,323,306 unique[3] voters across these three periods, with 17,391,433 who did not change residences from 2008-2012[4] (39% of 2008 registrants), 22,565,114 from 2012-2016 (49% of 2012 registrants), and 29,327,029 from 2016-2020 (59% of 2016 registrants). Unlinked voters either moved, de-registered, or failed to link. Some of the differences in proportion linked across years are due to decreases in residential mobility – 12.5% of people reported moving in 2008, down to 9.3% in 2020 (CPS, 2020). Projected across 4-year periods, the linkage rates reflect these mobility rates. Linkage details are provided in the Supporting Information (Section S1).

In the analysis, I focus on voters who do not change residences between elections. Comparing voters who do not change location makes for more accurate linkages, since voters are linked by residential address. This strategy also holds constant time-invariant features of neighborhoods, and avoids selection issues that arise from voters choosing where to move then choosing to change registration (see Cho, Gimpel, and Hui (2019)). For example, focusing on non-movers holds constant material differences between neighborhoods, such as moving to a wealthier neighborhood with higher property taxes. But this strategy does not completely solve selection issues. If the process that causes someone to stay in a neighborhood is the same process that causes someone to change their partisanship, then the results may be biased. One pattern that would be consistent with such bias would be if voters are more likely to move to a more co-partisan neighborhood in response to out-partisan change in their current neighborhood. In the Supporting Information (Section S2), I analyze mobility patterns for voters who change residences across the panel, finding that increased out-partisan exposure does not make voters more likely to move and movers tend to relocate to areas with similar partisan demographics – consistent with previous research demonstrat-

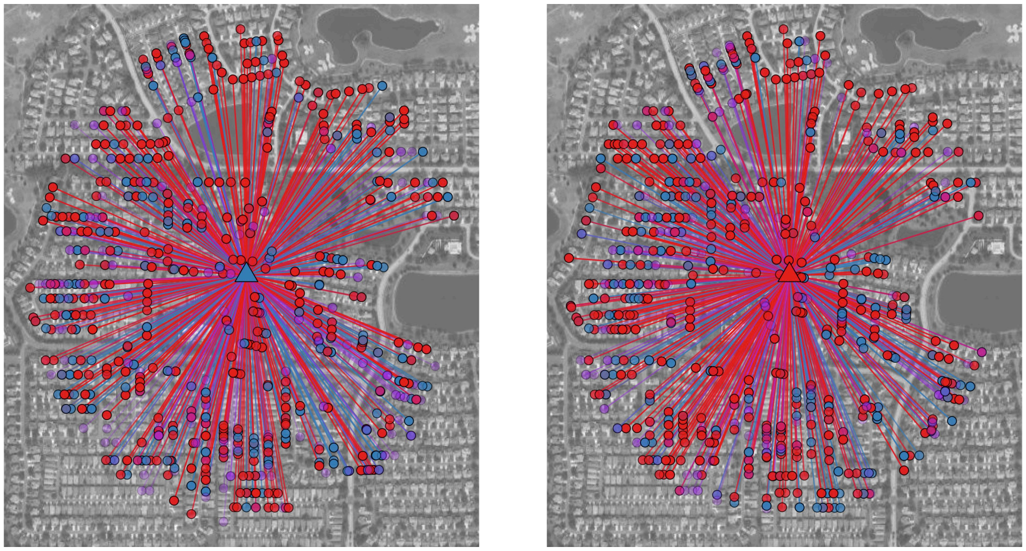
[3]Many voters appear in more than one linked sample, meaning they did not change residences across multiple presidential election cycles.

[4]I do not have 2008 voterfiles for each state. For the 2008-2012 linked sample, I use the California 2007, Florida 2007, Kansas 2008, New York 2008, and North Carolina 2009 voterfiles.

ing that mobility decisions are largely divorced from partisan context (Mummolo and Nall, 2017; Martin and Webster, 2018).

Measuring Partisan Context

Normally, exposure is measured using aggregate summaries from areal units, assuming that every person living in a unit has the same level of exposure. But two voters living in even the same neighborhood can have different levels of exposure to Democrats and Republicans (Brown and Enos, 2021). Testing local influence is best served by measures of partisan geography that capture where voters live in relation to other voters. Using data on the addresses of every voter and their registered neighbors, I construct *spatial exposure* statistics developed in Brown and Enos (2021), identifying each voter's 1,000 nearest neighbors in the voterfile, and calculating the distance in meters that they live from each neighbor. I do this for all voters in each state-year file, and calculate the weighted proportion of their 1,000 nearest neighbors who are registered Democrats and Republicans, weighting by the inverse of the distance they live from each neighbor. Thus, I am giving greater weight to neighbors who live closest to each voter. Figure 1 illustrates this process, plotting the 1,000 most proximate neighbors for a Democrat in Wildwood, FL who switched to Republican after increased Republican exposure from 2016 to 2020. While the overall balance of neighbors shifts Republican, the most noticeable shift is those living closest to the voter. This highlights the importance of weighting by proximity to capture changes in local exposure.



2016 2020

Figure 1: Partisan Exposure Maps

Maps plot nearest registered neighbors at the latitude and longitude coordinates of each residential address. Democrats are colored blue, Republicans red, and non-partisans purple. The voter saw a 0.42 to 0.63 increase in Republican exposure and a commensurate decrease (0.38 to 0.18) in Democratic exposure.

Let $DE_{i,t}$ and $RE_{i,t}$ be Democratic and Republican exposure for voter i in year t. Let $\mathcal{N}_{i,t}$ be the set of 1,000 registrants who live closest to voter i in year t, $D_{i,j,t}$ the distance[5] in meters between voter i and neighbor j in year t, and $Y_{j,t}$ the partisan registration of neighbor j in year t. Partisan exposure is defined as:

$$DE_{i,t} = \frac{\sum_{j \in \mathcal{N}_{i,t}} \frac{1}{D_{i,j,t}} \mathbb{I}(Y_{j,t} = \text{Democrat})}{\sum_{j \in \mathcal{N}_{i,t}} \frac{1}{D_{i,j}}}$$

$$RE_{i,t} = \frac{\sum_{j \in \mathcal{N}_{i,t}} \frac{1}{D_{i,j,t}} \mathbb{I}(Y_j = \text{Republican})}{\sum_{j \in \mathcal{N}_{i,t}} \frac{1}{D_{i,j}}}$$

This measure offers several advantages. First, by calculating exposure with each voter at the center of their 'neighborhood', this measure is unique to each voter. Second, this measure

[5] $D_{i,j}$ is adjusted up 1 to avoid dividing by zero.

incorporates precise information about where voters live in relation to each of their neighbors. In these ways this metric avoids common measurement issues that arise from aggregation (Openshaw, 1983). One limitation of this measure is that non-partisan neighbors may have a partisan lean that is not accounted for by registration data. I rely on registration to avoid measurement error in imputing partisanship for voters not registered Democrat or Republican. Additionally, a registered Democrat or Republican neighbor sends a stronger signal to conform by joining that party than one who votes for that party's candidates but chooses not to explicitly affiliate. This measure is also limited in that it cannot account for unregistered neighbors, but I include controls for Census Block Group proportion registered in the estimation to account for the influence of changes in registration.

In the Supporting Information (Section S6.4) I demonstrate the robustness of the results to other neighborhood definitions, including not accounting for distance between neighbors, neighborhoods defined by 100 and 500 nearest neighbors, by neighbors within one mile from the voter, and by Census Block and Census Block Group. The results are also consistent when dropping same household neighbors[6], and when dropping non-partisan neighbors – calculating exposure to Democrats or Republicans out of total partisan neighbors.

Registration and Exposure Trends

Voters in the linked samples exhibit high levels of partisan stability. Figure 2 reports rates of party switching across presidential elections. Just 5.7% of voters in 2008, 2012, and 2016 are registered to a different party 4 years later. Figure 3 plots the within-individual changes in exposure for the 2008-2012, 2012-2016, and 2016-2020 panels. The distributions are centered at approximately zero, but there is variation in the types of neighborhood changes that voters

[6] There are several reasons to consider the results without same household neighbors. First, this measure of spatial exposure can be sensitive to the inclusion of registrants listed at the same address as a voter in the calculation of that voter's partisan exposure, as their high proximity grants them strong influence on the metric (Brown and Enos, 2021). Second, while cohabitants are an important feature of a voter's geographic context, they likely represent a different type of local tie than a neighbor at a different address.

experience across time, with many voters seeing large increases or decreases in exposure.

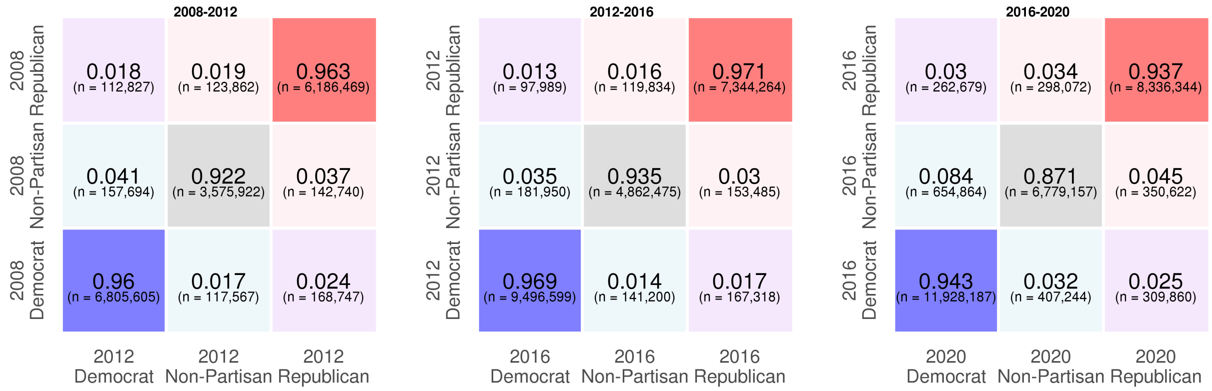
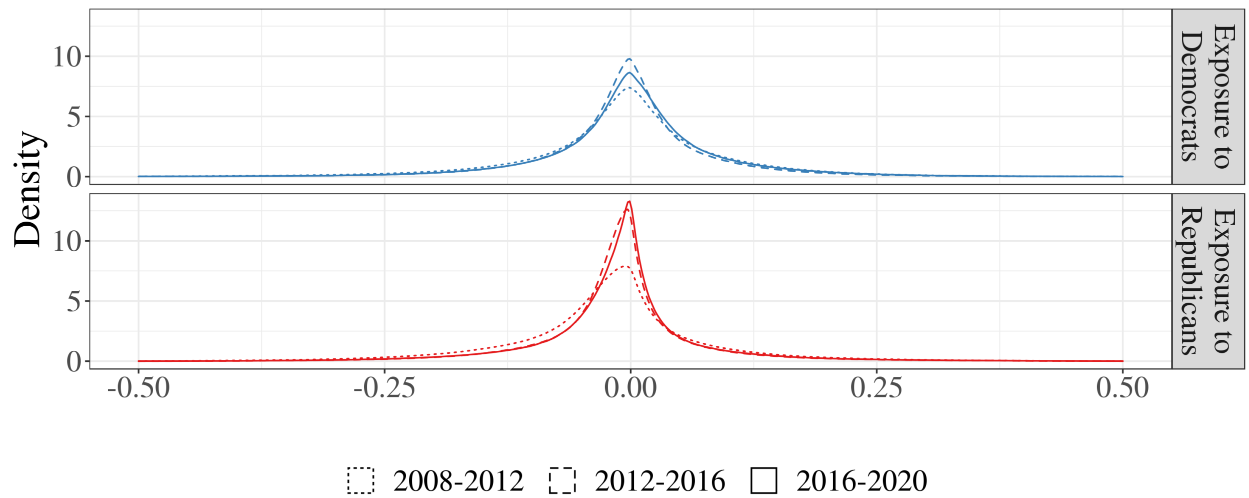


Figure 2: Partisan Transition Matrices

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.



	2008-2012			2012-2016			2016-2020		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
Exposure to Republicans	-0.02	-0.02	0.11	-0.01	-0.01	0.09	-0.01	-0.01	0.10
Exposure to Democrats	0.00	0.00	0.11	0.00	0.00	0.09	0.00	0.00	0.10

Figure 3: Distribution of Changes in Democratic and Republican Exposure

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.

Panel Empirical Strategy

With the panel data, I measure the effect of changing Democratic and Republican exposure on partisan registration, examining changes across the 2008-2012, 2012-2016, and 2016-2020 presidential election cycles. The size and scope of the voterfile data allow for precise comparisons through matching on voter characteristics, treatment histories, and pre-treatment outcomes in order to make more credible causal inferences. In doing so, I try to best approximate the ideal comparison of two individuals who are similar on all characteristics, are registered to the same political party, and have chosen to live in the same general area and in similar types of neighborhoods, and then see how their behavior differs as one's closest neighbors change but the other's remain static. With this setup, I test my central hypothesis:

Partisan Conversion: Increased exposure to Democratic (Republican) neighbors makes voters more likely to register as Democrats (Republicans).

I compare within-voter changes in partisan registration across voters who experience different changes in partisan context. I estimate these effects using a first differences model, measuring the effect of 4-year changes in Democratic or Republican exposure from 2008-2012, 2012-2016, and 2016-2020 on changes in Democratic or Republican registration. I estimate these effects on current and future registration changes, measuring the effect on voters changing partisanship in the same time period and in the following 4 years (i.e. the effect of 2012-2016 exposure changes on 2016-2020 partisanship changes).[7]

To better isolate the effect of exposure on registration, I create strata defined by the full interaction of voter race, gender, marital status, age decile, Zip Code, and Democratic or Republican exposure decile in the first election year. I include these strata as a fixed effect in the estimation, so I am estimating effects for voters matched on these individual and geographic characteristics. I also subset by political party in the first election year, so I am estimating effects separately for subsets defined by original partisanship.

These strata provide a powerful comparison. Zip Codes generally capture the same town or part of a town, and voters living in the same Zip Code usually share federal and state representatives, mayoral leadership, local labor market conditions, property tax systems, and other political and economic features determined at geographies at or above Zip Codes

[7]Since there is no downstream election cycle following 2016-2020 in the data, I do not estimate future effects for this treatment period.

(USPS, 2013). Thus, when comparing voters in the same Zip Code, the influence of many localized political shocks that might produce spatially clustered partisan switching and overall changes in neighborhood composition is constant across voters, as are characteristics leading voters to live in this same small geography. This matching strategy thus limits confounding concerns to localized shocks or trends that are operating within-Zip Code, *and* are independent from race, age, gender, and starting levels of exposure to Democrats or Republicans.

To account for other contextual trends, I control for changes in Block Group[8] income, employment, racial demographics, median age, housing values, renter versus homeowner proportions, median year that houses were built, proportion of the population that drives to work, proportion college educated, and the proportion of the population that is registered to vote. I also account for individual changes in marital status during the time period by controlling for the difference in binary variables for married in the first and second election years.[9]

Let $D_{i,t}$ denote a binary variable that takes 1 if voter i is a registered Democrat in election year t and 0 otherwise. Let $DE_{i,t}$ denote a continuous variable measuring the spatially weighted proportion of Democrats in the 1,000 nearest neighbors of voter i in election year t, and $\boldsymbol{X}_{i,t}$ denote a vector of time-varying Block Group covariates. Let α_M be the strata fixed effect and $\epsilon_{i,c}$ the error term (clustered at the county-level). I estimate regressions of the form[10]:

[8] I use 5-year American Community Survey data where the final year is the voterfile data year. For 2020, for which data are not yet available, I use the 2015-2019 ACS. For 2008, I use the 2006-2010 ACS, which provides the data using 2010 Block Group definitions.

[9] Block group college education and unemployment are not available for the 2008 data, so I do not use these variables in the 2008-2012 estimation. Older state files also do not have marital status, so that variable is not used for the 2008-2012 sample.

[10] For the future effects, the specification is the same on the right-hand side, but the outcome is $D_{i,t+2} - D_{i,t+1}$.

$$D_{i,t+1} - D_{i,t} = \alpha_M + \theta(DE_{i,t+2} - \mathrm{DE}_{i,t}) + \boldsymbol{\beta}(\boldsymbol{X}_{i,t+1} - \boldsymbol{X}_{i,t}) + \epsilon_{i,c} \tag{1}$$

I also estimate the effect of Republican exposure on Republican registration, swapping out $D_{i,t}$ and $DE_{i,t}$ for $R_{i,t}$ and $RE_{i,t}$ (Republican partisanship and Republican exposure) and using Republican exposure decile to define α_M. θ represents the effect of one unit increase in Democratic (Republican) exposure on changes in Democratic (Republican) registration.

Identifying Assumptions

There are several threats to inference that must be considered in order to interpret these estimates 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 accounting for other time-variant features of neighborhoods using Block Group contextual controls. 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, I match on individual and contextual variables to narrow the scope of my comparison to compare most similar individuals. I also estimate alternative specifications using matched pre-trend strata defined by partisan registration and coarsened partisan exposure in the years preceding the start of the panel. Due to pre-trend data availability this specification is only estimated for the 2012-2016 and the 2016-2020 linked samples. Pre-trends for the 2012-2016 data come from the older voterfiles linked to the Target Smart panel.[11] Pre-trends for the 2016-2020 data come from 4 prior years of Target Smart data (2012-2015). This specification is restricted to voters who lived at the same residence and were registered in the pre-trend years. This design is akin to previous analyses that match on pre-trends (i.e. Hall and Yoder (2021)).

Identification is complicated by the fact that a voter who switches registration will influence the treatment of a different voter to whom they are a neighbor. In the current effects, where treatment is measured across the same time period as the outcome, if many proximate voters are changing their registration for reasons that are unrelated to local influence, the estimation will still recover a positive correlation (Manski, 1993). To the extent that this spatially clustered partisan switching is occurring independent from the matching variables in the main specification or the treatment and outcome trends in the pre-trend specification, then the effect will be biased. The future effects, however, are not subject to this automatic correlation, since treatment and outcome are measured in different time periods.

To examine the sensitivity of the current effects to within-Zip Code confounding, I conduct a simulation measuring how much within-Zip Code party switching would have to occur for the estimation strategy to return estimates of the same size as the effects. The simulation demonstrates that estimation is sensitive to within-Zip Code switching, but to fully explain the effects the level of party switching generated by within-Zip Code shocks would have to be large enough to generate 1.5-3 times as many changes in partisanship as occur in the data. Simulation details are provided in Supporting Information Section S5.

[11] Older voterfile coverage varies by state. California pre-trends are constructed from 3 years of data (2005, 2007, 2009), Florida pre-trends from 2007 and 2009 voterfiles, Kansas from 2008 data, New York from 2001 and 2008 voter records, and North Carolina from 2009 data.

Effect of Partisan Exposure on Partisan Registration

Across election cycles and regardless of original partisanship, increases in Democratic (Republican) exposure increases the likelihood of registering as a Democrat (Republican). Figure 4 presents the current effect estimates from the main and pre-trend matching specifications, plotting the effect of changing Democratic exposure on a voter's likelihood of being registered as a Democrat at the end of each panel, and the effect of the same change in Republican exposure on being registered Republican, for the 2008-2012, 2012-2016, and 2016-2020 linked samples. The effect of Democratic exposure on Democratic partisanship for voters who were originally Non-Partisans or Republicans is the effect on switching to Democrat. The effect of Democratic exposure on Democratic partisanship for voters who were originally Democrats is the effect on remaining a Democrat. Likewise, the effect of Republican exposure is the effect on switching for voters who were originally Non-Partisans or Democrats, and is the effect on remaining Republican for voters who were originally Republicans.

The coefficients represent the effect of a 100 percentage point exposure increase, but a more intuitive consideration of the results is that an approximately one standard deviation, or 10 percentage point increase, in Democratic or Republican exposure leads to a 1-3 percentage point increase in the likelihood of registering with that party, depending on year and subset. Across the linked samples, 5.7% of voters change their party registration between presidential election cycles, so these effects constitute a 20%-60% increase over the baseline probability of changing party.

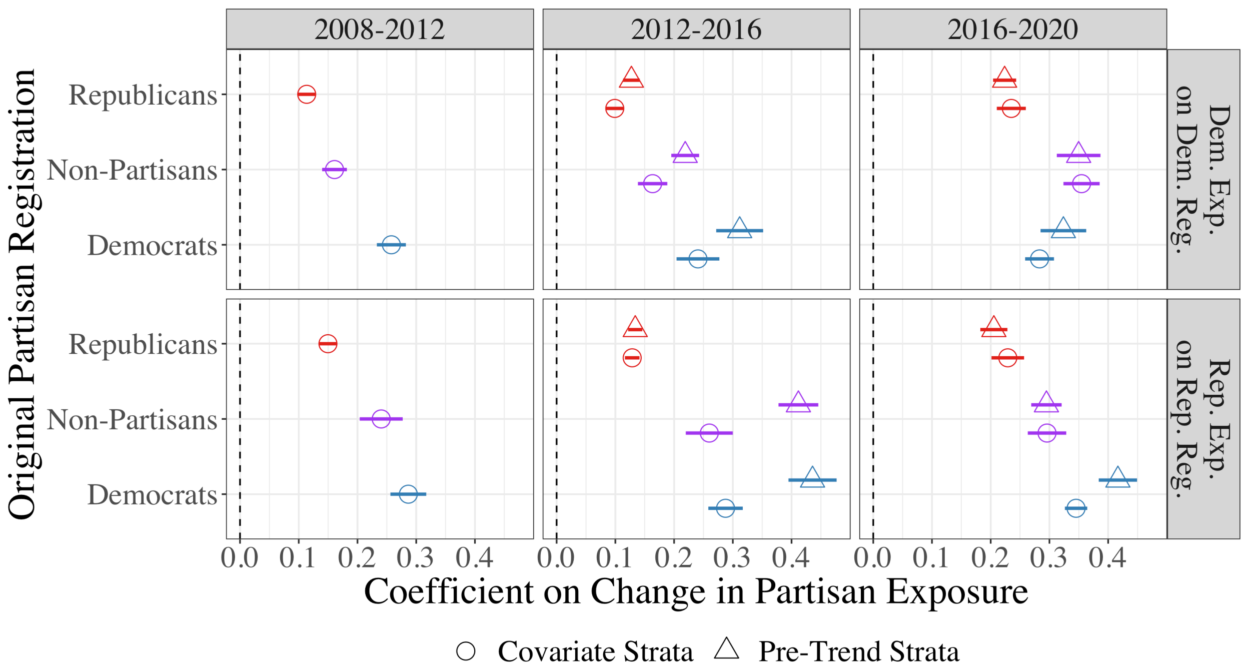


Figure 4: Effect of Partisan Exposure on Partisan Registration – Current Effects

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), separately for the 2008-2012 (left column), 2012-2016 (middle column), and 2016-2020 (right column) linked samples. Results represent the effect of changing exposure during the treatment period on changes in partisan registration during the same period. Results are plotted separately for subsets based on partisanship in the first year of the linked sample. Circular points plot coefficients from main specification and triangular points plot coefficients from pre-trend specifications. Bars plot 95% confidence intervals.

Figure 5 plots the future effects. A 10 percentage point increase in Democratic or Republican exposure from 2008-2012 causes a 0.3-0.6 percentage point increase in switching to that party between 2012-2016, while such an increase from 2012-2016 spurs a 0.9-1.3 percentage point increase in party switching from 2016-2020. Thus changes in partisan exposure produce both contemporary and downstream influences on party registration.

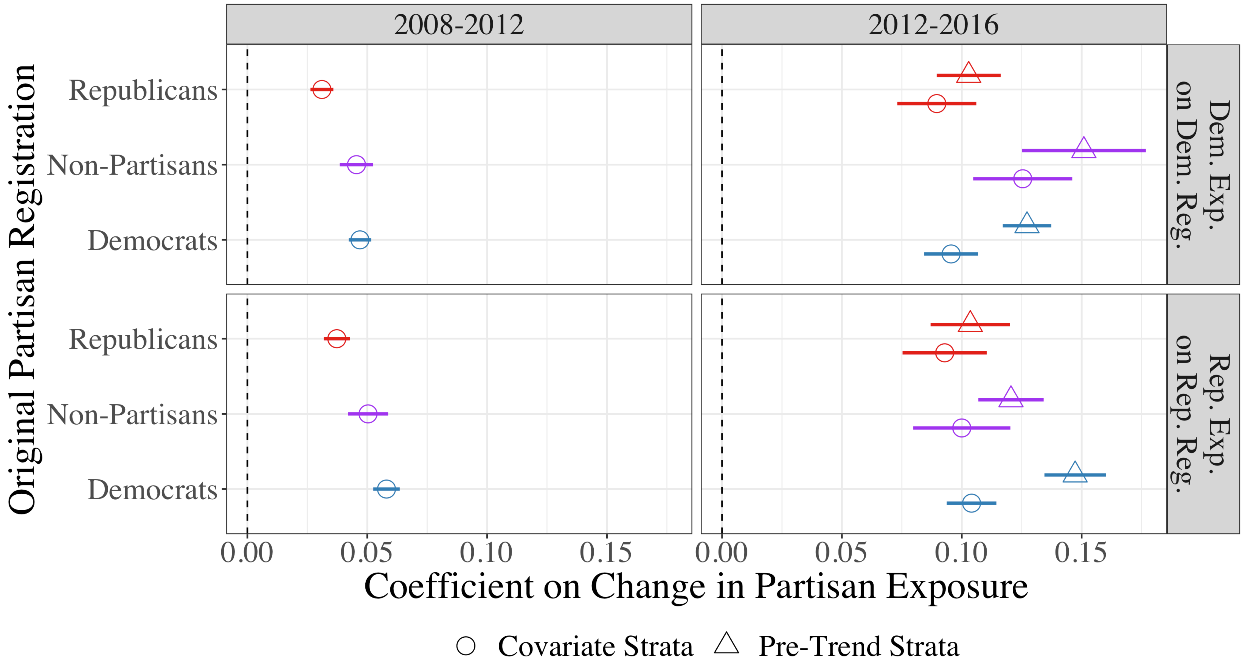


Figure 5: Effect of Partisan Exposure on Partisan Registration – Future Effects

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), separately for the 2008-2012 (left column), 2012-2016 (middle column), and 2016-2020 (right column) linked samples. Results represent the effect of changing exposure during the treatment period on changes in partisan registration during 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 main specification and triangular points plot coefficients from pre-trend specifications. Bars plot 95% confidence intervals.

For both the current and future effects, pre-trend strata specifications return similar estimates as the main specifications. As an additional test of the parallel trends assumption, I estimate pre-treatment period placebo trends by estimating the effect of changes in partisan exposure from 2016 to 2020 on individual Democratic and Republican registration in 2012-2015. I do so using the main specification, matching individuals on 2016 covariates. Figure 6 plots the effects on the placebo outcomes. Changes in partisan exposure from 2016-2020 are not predictive of past trends in partisanship, with these coefficients close to zero.

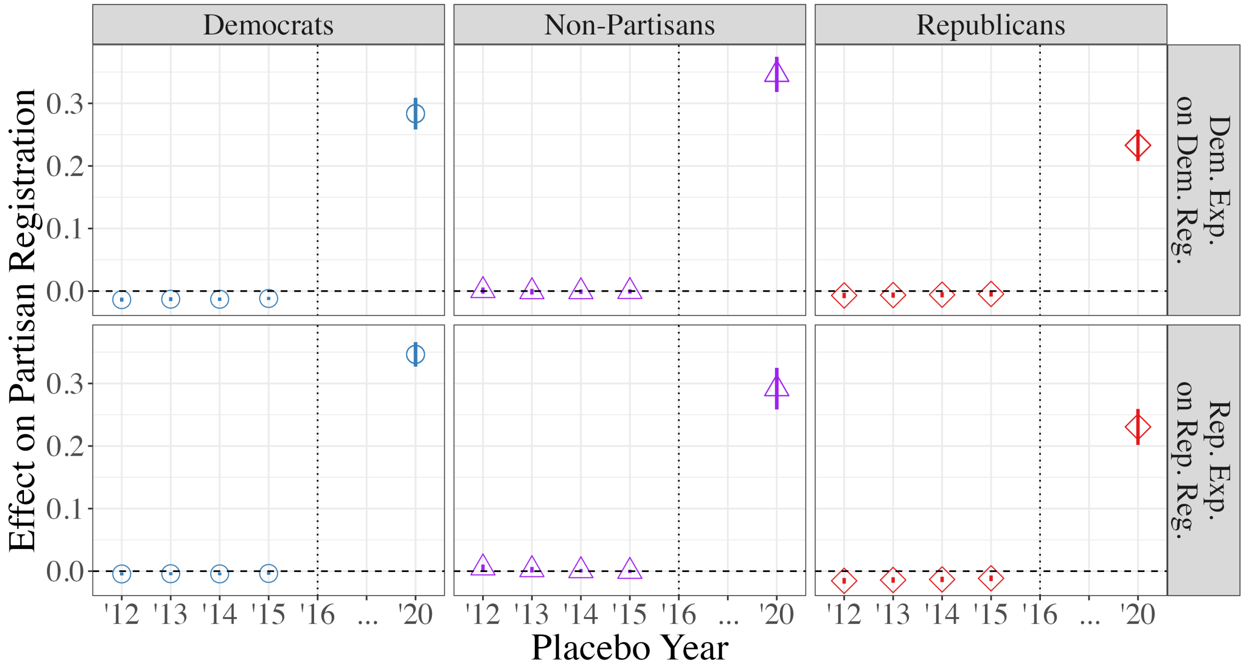


Figure 6: Placebo Trends

Figure plots effect of a one unit increase from 2016-2020 in Democratic exposure on Democratic partisanship (top row) and effect of a similar increase in Republican exposure on Republican partisanship (bottom row). The X-axis is the year the outcome is measured, though treatment is always measured as the change in partisan exposure from 2016-2020. So the points at 2012 represent the estimated effect of 2016-2020 changes in partisan exposure on 2012 partisanship. The 2020 current effect is included as a reference to compare to the placebo outcomes. Results are plotted separately for subsets based on partisanship in 2016. Bars plot 95% confidence intervals.

Neighbor Influence is Largest for Voters Most Connected to their Neighborhoods

In the theory section I detail effect heterogeneity that would be consistent with the panel effects being due to social influence. 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 7 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. I estimate the effects for age and housing subsets together because age is correlated with housing type, and I want to demonstrate that heterogeneity across either characteristic is not driven by the other. The results are larger for voters living in single-family homes, while the effects for voters in apartments are muted. The effects are consistently increasing by age within the single-family home group, but do not vary substantially by age for voters in apartments. The effects for 2012-2016 are similar, and are shown in Supporting Information Section S6.5, as are the results subset to Whites, to show the patterns are not due to differences in race across age groups or housing type.

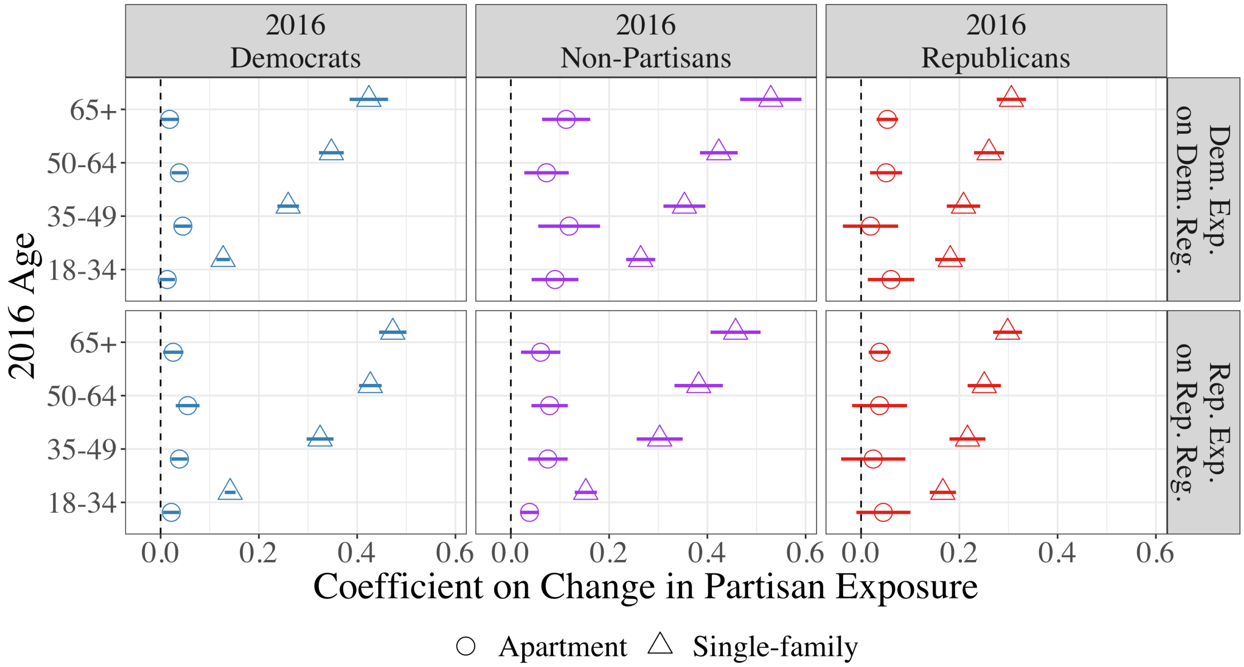


Figure 7: Effect of Partisan Exposure by Age and Housing Type

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 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.

That older voters are most influenced by partisan exposure seems in contrast with the general consensus that partisan stability increases with age (Franklin and Jackson, 1983; Alwin and Krosnick, 1991; Sears and Funk, 1999). But while older voters are less likely overall to change partisanship, they experience a greater increase in party switching from partisan exposure. Since older voters are more likely to express trust in their community and report knowing their neighbors (Parker et al., 2018), this heterogeneity suggests that the effects of partisan exposure are largest for voters more likely to be connected to their community, which is consistent with the effects being driven by social influence. Variation by housing type suggests that whether voters are influenced by those they live near depends on how communities are physically organized. Social influence operates through mechanisms of observance and interaction, both of which may be stronger when voters live across the street from, rather than on top of, one another.

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 the interaction coefficient should be positive. 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.

These models are of the form:

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

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.

Figure 8 plots the interaction coefficients from these models for subsets of voters who were originally Democrats, Republicans, or Non-Partisans in the 2012-2016 and 2016-2020 linked samples. The interaction coefficients from the models with White interacted with White partisan exposure are consistently positive, meaning that exposure to White partisans 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 those interaction coefficients for Blacks and exposure to Black partisans are generally null, possibly due to higher Democratic stability among Black voters.

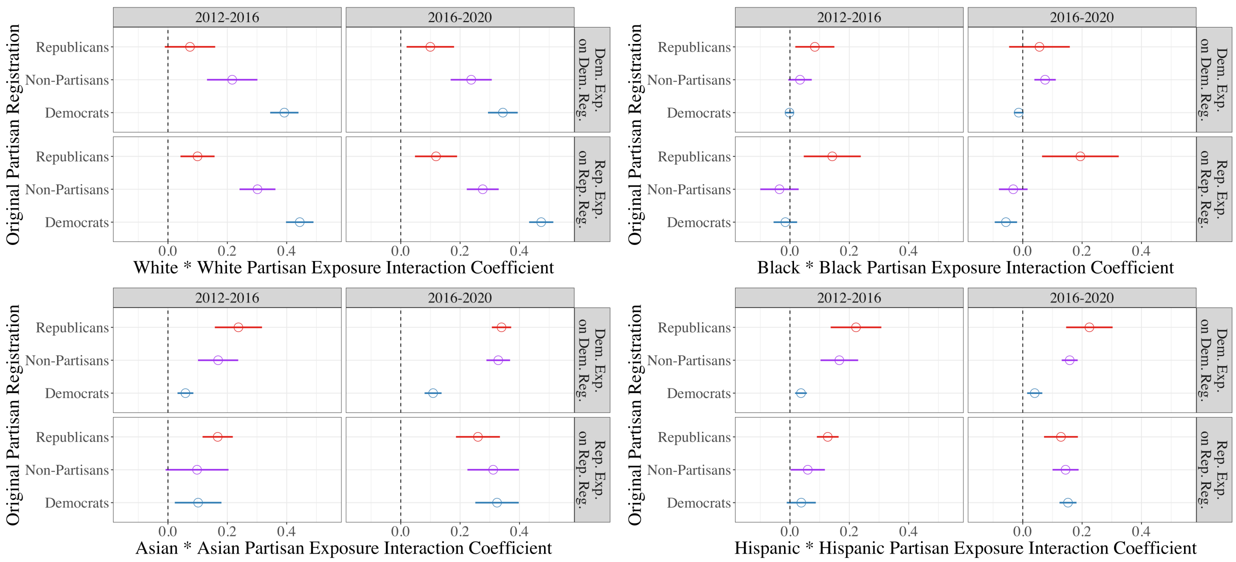


Figure 8: Voters are Most Influenced by Same-Race Neighbors

Top left figure plots the coefficient for the interaction between whether a voter is White and exposure to White Democrats or White Republicans, from the current effect specifications. Points represent the difference between Whites and non-Whites in the effect of a one unit increase in exposure to White Democrats on Democratic partisanship (top row) and effect of a similar increase in exposure to White Republicans on Republican partisanship (bottom row), separately for the 2012-2016 (left column), and 2016-2020 (right column) linked samples. 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. Results are plotted separately for subsets based on partisanship in the first year of the linked sample. Bars plot 95% confidence intervals.

These results suggest that the strength of partisan influence depends on being similar to one's neighbors along other dimensions, particularly race. A voter who changes party in response to increased partisan exposure is seeking political commonality with people they are similar to along other – in this case geographic – dimensions. This influence should thus be stronger if other identities are also shared with neighbors. Racial similarity may be particularly important in this context due to the prevailing impact of race on geographic interaction (Putnam, 2007) and in determining partisanship (Mangum, 2013; Hajnal and

Rivera, 2014).

Survey Evidence of Social Influence

The panel data demonstrate that shifts in local partisan composition influence voters to change registration to match local partisanship. But these data cannot measure how voters perceive local geography, and how partisan attitudes are shaped by exposure. To gather such information, I conduct an original survey of voters from the panel. With these data, I measure how voters perceive and experience their neighborhoods: do they think they live near Democrats/Republicans and do they have contact with Democrats/Republican neighbors? I also test whether voters feel social pressure to appear politically similar to their neighbors, asking how comfortable they would be with neighbors knowing their partisanship. Lastly, I measure how voters view the parties – perceptions of Democratic and Republican party ideology and feelings of favorability towards Democrats and Republicans – and whether these views are moderated by partisan exposure. Thus, these survey questions examine the causal process by which changes in partisan exposure may lead to changes in partisan registration: local geography changes, voters perceive the partisan norms around them and come into contact with partisan neighbors, they feel social discomfort if they are politically different from local norms, and alter their opinion about the parties.

Survey Data

The survey was in the field from June 29, 2020 to August 28, 2020, administered via email and conducted online. Potential respondents were drawn from e-mail lists connected to voterfile data by Target Smart. Voters were randomly drawn from the email list, but an oversample was taken in the 5 states from the panel analysis. The response rate for the survey was 1.57%, similar to typical single-digit rates from phone or email surveys. Since voters are surveyed off the voterfile, I connect survey responses to individual partisan exposure. The survey also contains questions on demographics, partisanship, strength of partisanship, and ideology.

Table 1 reports the survey outcomes used in the main analysis, and the scales of each outcome. To measure geographic perceptions, respondents were asked whether their neighbors are "All Republicans, nearly all Republicans, more Republicans than Democrats, evenly Democrats and Republicans, more Democrats than Republicans, nearly all Democrats, or all Democrats." Contact with Democratic and Republican neighbors is measured by asking respondents whether they have personal contact with neighbors from the Democratic and Republican party, with response options following a 7 point ordinal scale from "None/not at all" to "A great deal". These two questions measure how voters perceive and experience their local geography, with the expectation that if voters respond to partisan exposure by changing their party, then they should say they live around more Democrats/Republicans and report greater contact with partisan neighbors when they have more neighbors from that party.

Table 1: Survey Outcomes

Survey Outcome	Scale
More Democrat or Republican neighbors	All Rep. – All Dem. (1 - 7)
Contact with Democrat neighbors	None – A great deal (1 - 7)
Contact with Repuplican neighbors	None – A great deal (1 - 7)
Share PID with neighbors	Very uncomfortable – Very comfortable (1 - 5)
Democrat Party ideology	Very conservative – Very liberal (1 - 7)
Republican Party ideology	Very conservative – Very liberal (1 - 7)
Feeling thermometer: Democrats	Very unfavorable – Very favorable (0 - 100)
Feeling thermometer: Republicans	Very unfavorable – Very favorable (0 - 100)

Comfort with sharing partisanship with neighbors is measured by asking "How comfortable would you be if your neighbors knew which political party you preferred? Very uncomfortable, somewhat uncomfortable, neutral, somewhat comfortable, very comfortable". This survey question tests one mechanism, social pressure, by which voters may be incentivized to conform in response to partisan exposure. If voters are less comfortable with the idea of their neighbors knowing their partisanship when they live around more out-partisan neighbors, then this would suggest that voters are sensitive to the political judgements of their neighbors.

Perceived party ideology is measured on a 7 point scale from "Very conservative" to "Very liberal". Favorability towards Democrats and Republicans is measured through feeling thermometers on a 0 to 100 scale. These questions capture how voters view parties (how ideologically extreme are the parties?) and how they feel about party members (do they like Democrats/Republicans?), to test whether voters are more amenable towards a party when they live around more neighbors from that party.

Survey Estimation

I limit the analysis to respondents who are in the 2016-2020 linked sample and who verified their identity in the survey, leaving 24,623 respondents. I model the relationship between 2020 Democratic and Republican exposure and survey outcomes, using weighted least squares regressions, weighting by survey weights.[12] I control for individual (race, age, gender, educational attainment, homeowner status, years of residence in current home, ideology, partisan lean and marital status) and aggregate (Block Group % White, median age, unemployment rate, median household income, % college educated, % drive to work, median year housing built, median house value, and % registered) characteristics, and include Zip Code fixed

[12]Details on the construction of the weights are provided in the Supporting Information (Section S7.2), as are the results without weights, which are consistent with the weighted results.

effects. I estimate regressions of the form:

$$Y_i = \theta \text{DE}_i + \boldsymbol{\beta} \boldsymbol{X}_i + \gamma_z + \epsilon_{i,c} \tag{2}$$

where Y_i is the outcome variable, $\boldsymbol{X}_i$ is the vector of covariates, γ_z is the Zip Code fixed effect. Standard errors are clustered at the county-level.

Survey Results

Table 2 presents the results from the models[13] for perceptions of neighbors' partisanship, interaction with partisan neighbors, and comfort sharing partisanship with neighbors. The coefficient on Democratic exposure in Model 1 is positive, meaning that Democratic exposure predicts reporting that one's neighborhood is more Democratic than Republican. The reverse relationship is seen for the coefficient on Republican exposure in Model 2. Models 3 and 4 demonstrate that there is a positive relationship between Democratic exposure and contact with Democratic neighbors, and an even larger association between Republican exposure and contact with Republican neighbors.

In Models 5 and 6, I interact[14] Democratic and Republican registration with Democratic and Republican exposure, respectively, to see if there are differential effects by registration of partisan exposure on comfort with neighbors knowing one's partisanship. Voters are more likely to express such comfort when they live around more neighbors who share their party, suggesting that voters are sensitive to the social pressure from local partisan norms. The coefficient represents the predictive effect of partisan exposure net of other demographic and

[13] Discrepancies between survey size and number of observations in the models is due to respondents not being asked every question, and to voters skipping questions or selecting "Prefer not to say" on demographic questions.

[14] Models 5 and 6:

$$Y_i = \theta DE_i + \tau D_i \times DE_i + \boldsymbol{\beta} \boldsymbol{X}_i + \boldsymbol{\eta} D_i \times \boldsymbol{X}_i + \gamma_z + \epsilon_{i,c}$$

Table 2: Partisan Exposure on Perceptions of Neighbors' Partisanship, Interaction with Partisan Neighbors, and Comfort Sharing Partisanship with Neighbors

	Dem vs. Rep Neighbors		Contact Dems	Contact Reps	Comfort Share PID	
	(1)	(2)	(3)	(4)	(5)	(6)
Democratic Exposure	0.44		0.62		-0.34	
	(0.10)		(0.21)		(0.17)	
Democratic Exposure * Democrat					0.53	
					(0.21)	
Republican Exposure		-0.50		1.14		0.06
		(0.09)		(0.19)		(0.21)
Republican Exposure * Republican						0.54
						(0.23)
Mean Outcome	3.82	3.82	3.44	3.56	4.05	4.05
Num.Obs.	19,123	19,123	18,144	18,159	14,365	14,365
R^2	0.589	0.590	0.391	0.451	0.423	0.427
R^2 Adj.	0.497	0.500	0.247	0.322	0.252	0.257
Covars	✓	✓	✓	✓	✓	✓
FE: Zip Code	✓	✓	✓	✓	✓	✓

Table presents results from WLS regression modeling the relationship between Democratic and Republican exposure and perceptions of neighbors' partisanship, contact with Democratic or Republican neighbors, and level of comfort with neighbors knowing one's partisanship. Coefficients on Democratic or Republican exposure represent the change in the outcome corresponding to a 1 unit increase in exposure. Cluster-robust standard errors, clustered at the county level are show in parentheses.

individual characteristics, but it is possible that social pressure is intensified when considering the bundled nature of partisanship (i.e. the alignment of race and party) since these overlapping identities increase social distance between parties.

Table 3 reports the coefficients from the models testing the relationship between partisan exposure and perceptions of the political parties. Voters who live around more Democratic neighbors are less likely to describe the Democratic Party as "Very liberal" compared to those without local Democratic exposure. Republican exposure, however, is not predictive of ideological assessments of the Republican party. Democratic exposure is strongly predictive of positive favorability towards Democrats, and Republican exposure is similarly predictive of

Table 3: Partisan Exposure on Party Ideology and Partisan Favorability

	Dem Ideo	Rep Ideo	Dem Therm	Rep Therm
	(1)	(2)	(3)	(4)
Democratic Exposure	-0.29		9.82	
	(0.10)		(2.04)	
Republican Exposure		0.01		8.63
		(0.12)		(1.99)
Mean Outcome	5.86	2.14	49.26	46.02
Num.Obs.	21,159	21,144	18,886	18,850
R^2	0.533	0.444	0.794	0.777
R^2 Adj.	0.438	0.331	0.747	0.726
Covars	✓	✓	✓	✓
FE: Zip Code	✓	✓	✓	✓

Table presents results from WLS regression modeling the relationship between Democratic and Republican exposure and perceptions of party ideology and favorability towards Democrats and Republicans. Coefficients on Democratic or Republican exposure represent the change in the outcome corresponding to a 1 unit increase in exposure. Cluster-robust standard errors, clustered at the county level are show in parentheses.

pro-Republican favorability. Thus, voters who live around more Democrats think the Democratic Party is less ideologically extreme, and view Democrats more favorably, than those who live without Democratic neighbors. Voters who live around Republican neighbors do not necessarily change their perception of Republican party ideology, but nonetheless still express greater favorability towards Republicans. While the data cannot say exactly why partisan exposure seems to moderate views of Democratic but not Republican ideology, this difference may be due to asymmetry in the parties' ideological positions. Since the Republican party is measured as closer to the conservative extreme of the ideological distribution than the Democratic party is to the liberal extreme (Grossmann and Hopkins, 2016), the effect of Republican exposure on perceptions of Republican ideology may be constrained.

The survey results demonstrate that variation in partisan geography describes meaningful variation in political context for voters, influencing how they perceive their neighborhood, the rate at which they interact with members of each party, their comfort expressing their own partisanship, and their views of each party. As such, the results illustrate the causal sequence by which partisan exposure is internalized by voters, shapes partisan interaction, activates social pressure, and changes how voters view the parties, all of which may influence voters assessment of their own partisan affiliations.

Conclusion

U.S. partisan segregation has steadily increased since the 1970s, and by some accounts is higher than it has been at any point since the Civil War (Kaplan, Spenkuch, and Sullivan, 2022). These trends coincide with intensifying social and political differences between parties (Levendusky, 2009). This paper provides evidence on a key piece of missing information on how voters are influenced by local homogeneity, with implications for U.S. political segregation and partisan conflict: whether voters are influenced by the politics of those they live around, and align their partisanship to match local peers. Such partisan conversion has been posited by scholars of partisanship (Lazarsfeld, Berelson, and Gaudet, 1948), geographic sorting (Rodden, 2019; Martin and Webster, 2018), and neighborhood effects (Huckfeldt and Sprague, 1987), but has proven difficult to test due to measurement and identification challenges. But data connecting political outcomes to voters' exact locations demonstrate that partisanship and underlying political attitudes are shaped by where voters live and who they live close to. Local homogeneity produces political conformity, as voters are influenced to adopt neighbors' partisanship.

What drives these effects? Survey data support social influence mechanisms. Voters accurately infer neighbors' partisanship and report contact with the partisans they live near. Knowledge of local partisanship activates social pressure to conform, as voters are uncomfortable disclosing their partisanship when it does not cohere with neighbors'. In addition, voters hold more positive views of either party when they live near members of that party, indicating that exposure shifts partisan attitudes.

Subset analysis of the panel data further supports social influence, as the effects are most pronounced for voters most likely to be influenced by their neighbors: older voters who as a group report higher levels of community connection, voters in single-family communities where the built environment facilitates stronger social ties, and voters who see partisan exposure from same-race neighbors. Additional analyses find limited support for alternative explanations, such as campaign mobilization. For example, in the Supporting Information (Section S6.1), I estimate results separately by U.S. House district to see if the results are larger in competitive districts, where campaign mobilization efforts are more concentrated – but find results are similar across districts.

The size of the data allow for not just identification of statistically significant evidence of the conversion hypothesis, but interrogation of the substantive importance of effect sizes. In this regard, there are two contexts in which to consider effect magnitude. First, considering general levels of partisan change, are the effects evidence of a meaningful influence on voter psychology, and how do they compare to other influences on party switching? Partisanship is understood to be a stable marker of political identity, and thus small changes in partisanship represent relatively large shifts (Campbell et al., 1960; Green, Palmquist, and Schickler, 2004). In the data, voters change party infrequently, with approximately 5.7% of voters changing party between presidential elections. The effect of a one standard deviation increase in partisan exposure makes voters 1-3 percentage points more likely to adopt the party of their neighbors, a 20%-60% increase over the baseline probability of changing party. This represents a large relative increase in party switching, and can be compared to other influences on partisanship. Direct campaign contact asking voters to register with a party, for example, increases the likelihood of party registration by 8.9 percentage points (Gerber, Huber, and Washington, 2010). In another example, a family opioid overdose death increases Republican party defection by 1.2 percentage points (Kaufman and Hersh, 2020).

The effect of partisan exposure is lower than campaign contact, but similar to drug-related family deaths. Partisan geography is also more widespread than these other treatments, as voters are continuously influenced by those around them.

Second, how does social influence change partisan segregation? In the Supporting Information (Section S8), I simulated partisan switching from 2012-2020 as if partisan exposure does not influence party switching, to compare simulated (without social influence) segregation metrics – county-level partisan composition and dissimilarity index – to actual changes in segregation. In the five states of this study, geographic polarization within counties increased modestly from 2012-2020, with the average county dissimilarity index increasing by 1.17 percentage points (5% increase). Polarization across counties also increased, with counties that had more Democrats than Republicans in 2012 growing 3.2 percentage points more Democratic, and counties with more Republicans growing 2.0 percentage points more Republican. Based on the simulation, social influence accounted for 10.1% of the dissimilarity increase, 6.8% of the change in Democratic counties, and 2.9% of the shift in Republican counties. Thus, social influence is not a primary driver of geographic polarization, but has contributed to recent trends, making Democratic areas more Democratic, and Republican areas more Republican. Since residential mobility is also a minor influence on segregation (Mummolo and Nall, 2017; Martin and Webster, 2018), this points to other sources of realignment, such as generational change, as dominant factors driving geographic polarization.

Considering these impacts, partisan conversion may exacerbate ongoing partisan conflict. As behavioral conformity reinforces political segregation, parties will be even further representative of geographically distinct constituencies, driving ideological and issue polarization (Rodden, 2019). There are also fears that geographic isolation will worsen affective polarization, as geographic isolation limits exposure to competing political ideas, and voters increasingly view out-partisans as people who are regionally and culturally different (Cramer, 2016). The results in this paper validate these fears, showing that local interactions are meaningful, influencing how voters feel about the parties and their own partisanship. Furthermore, while exposure can reduce negative affect, conformity is more likely than co-existence, and as neighborhoods homogenize opportunities for cross-partisan contact will continue to diminish.

References

Abramowitz, Alan, and Jennifer McCoy. 2019. "United States: Racial Resentment, Negative Partisanship, and Polarization in Trumps America." *The ANNALS of the American Academy of Political and Social Science* 681(1): 137–156.

Abrams, Sameul J., and Morris P. Fiorina. 2012. "The Big Sort That Wasn't: A Skeptical Reexamination." *PS Political Science and Politics* 45(2): 203.

Ahler, Douglas J., and Gaurav Sood. 2018. "The Parties in Our Heads: Misperceptions about Party Composition and Their Consequences." *The Journal of Politics* 80(3): 964–981.

Alwin, Duane F., and Jon A. Krosnick. 1991. "Aging, Cohorts, and the Stability of Sociopolitical Orientations Over the Life Span." *American Journal of Sociology* 97(1): 169–195.

Anoll, Allison P. 2018. "What Makes a Good Neighbor? Race, Place, and Norms of Political Participation." *American Political Science Review* 112(3): 494508.

Berelson, Bernard, Paul Félix Lazarsfeld, and William N. McPhee. 1954. *Voting: a Study of Opinion Formation in a Presidential Campaign*. Chicago: University of Chicago Press.

Bobonis, Gustavo J., and Frederico Finan. 2009. "Neighborhood Peer Effects in Secondary School Enrollment Decisions." *The Review of Economics and Statistics* 91(4): 695–716.

Brown, Jacob R., and Ryan D. Enos. 2021. "The Measurement of Partisan Sorting for 180 Million Voters." *Nature Human Behaviour* .

Campbell, Angus, Phillip E. Converse, Warren. E. Miller, and Donald. E. Stokes. 1960. *The American Voter*. Chicago: University of Chicago Press.

Cantoni, Enrico, and Vincent Pons. 2021. "Does Context Trump Individual Drivers of Voting Behavior? Evidence from U.S. Movers." *Harvard Business School: Working Paper* .

Case, Anne C, and Lawrence F Katz. 1991. The Company You Keep: The Effects of Family and Neighborhood on Disadvantaged Youths. Working Paper 3705 National Bureau of Economic Research.

Chen, Jowei, and Jonathan Rodden. 2013. "Unintentional Gerrymandering: Political Geography and Electoral Bias in Legislatures." *Quarterly Journal of Political Science* .

Cho, Wendy K. Tam, James G. Gimpel, and Iris S. Hui. 2019. "Migration as an opportunity to register changing partisan loyalty in the United States." *Population, Space and Place* 25(4): e2218.

Cialdini, Robert B, Raymond R Reno, and Carl A Kallgren. 1990. "A focus theory of normative conduct: recycling the concept of norms to reduce littering in public places." *Journal of personality and social psychology* 58(6): 1015.

CPS. 2020. "Current Population Survey, Table A-1. Annual Geographic Mobility Rates, By Type of Movement: 1948-2020.".

Cramer, Katherine J. 2016. *The Politics of Resentment: Rural Consciousness in Wisconsin and the Rise of Scott Walker.* University of Chicago Press.

Druckman, James N., and Donald P. Green. 2013. "Mobilizing Group Membership: The Impact of Personalization and Social Pressure e-Mails." *SAGE Open* 3(2): 2158244013492781.

Enos, Ryan D. 2017. *The Space Between Us: Social Geography and Politics.* New York: Cambridge University Press.

Eubank, Nicholas, and Jonathan Rodden. 2020. "Who Is My Neighbor? The Spatial Efficiency of Partisanship." *Statistics and Public Policy* 7(1): 87–100.

Fischer, Claude S. 1982. *To Dwell Among Friends: Personal Networks in Town and City.* University of Chicago Press.

Franklin, Charles H., and John E. Jackson. 1983. "The Dynamics of Party Identification." *The American Political Science Review* 77(4): 957–973.

Gay, Claudine. 2004. "Putting Race in Context: Identifying the Environmental Determinants of Black Racial Attitudes." *American Political Science Review* 98(4).

Gerber, Alan S., Donald P. Green, and Christopher W. Larimer. 2008. "Social Pressure and Voter Turnout: Evidence From a Large-Scale Field Experiment." *American Political Science Review* 102(February): 33–48.

Gerber, Alan S, Gregory A Huber, and Ebonya Washington. 2010. "Party Affiliation, Partisanship, and Political Beliefs: A Field Experiment." *American Political Science Review* 104(04): 720–744.

Goldenberg, Jacob, and Moshe Levy. 2009. "Distance Is Not Dead: Social Interaction and Geographical Distance in the Internet Era." *CoRR* abs/0906.3202.

Green, Donald P., Bradley Palmquist, and Eric Schickler. 2004. *Partisan Hearts and Minds.* New Haven, CT: Yale University Press.

Green, Donald P, Jonathan S Krasno, Alexander Coppock, Benjamin D Farrer, Brandon Lenoir, and Joshua N Zingher. 2016. "The effects of lawn signs on vote outcomes: Results from four randomized field experiments." *Electoral Studies* 41: 143–150.

Grossmann, M., and D.A. Hopkins. 2016. *Asymmetric Politics: Ideological Republicans and Group Interest Democrats.* Oxford University Press.

Hajnal, Zoltan, and Jessica Trounstine. 2014. "What Underlies Urban Politics? Race, Class, Ideology, Partisanship, and the Urban Vote." *Urban Affairs Review* 50(1): 63–99.

Hajnal, Zoltan, and Michael U. Rivera. 2014. "Immigration, Latinos, and White Partisan Politics: The New Democratic Defection." *American Journal of Political Science* 58(4): 773–789.

Hall, Andrew B., and Jesse Yoder. 2021. "Does Homeownership Influence Political Behavior? Evidence from Administrative Data." *Journal of Politics* .

Henderson, Marlone D. 2009. "Psychological Distance and Group Judgments: The Effects of Physical Distance on Beliefs about Common Goals." *Personality and Social Psychology Bulletin* 35: 1330–1341.

Hersh, Eitan. 2015. *Hacking the Electorate: How Campaigns Perceive Voters*. Cambridge, UK: Cambridge University Press.

Highton, Benjamin, and Cindy D. Kam. 2011. "The Long-Term Dynamics of Partisanship and Issue Orientations." *The Journal of Politics* 73(1): 202–215.

Hobbs, William R. 2019. "Major Life Events and the Age-Partisan Stability Association." *Political Behavior* 41(September): 791–814.

Hopkins, Daniel J., and Thad Williamson. 2010. "Inactive by Design? Neighborhood Design and Political Participation." *Political Behavior* 34(1): 79–101.

Huckfeldt, Robert, and John Sprague. 1987. "Networks in Context: The Social Flow of Political Information." *American Political Science Review* 81(4): 1197–1216.

Hutchings, Vincent L, and Nicholas A Valentino. 2004. "The Centrality of Race in American Politics." *Annual Review of Political Science* 7: 383–408.

Imai, Kosuke, and Kabir Khanna. 2016. "Improving Ecological Inference by Predicting Individual Ethnicity from Voter Registration Records." *Political Analysis* 24(2): 263272.

Kaplan, Ethan, Jorg L. Spenkuch, and Rebecca Sullivan. 2022. "Political Sorting in the United States: A Comprehensive Theoretical and Empirical Overview.".

Kaufman, Aaron R., and Eitan D. Hersh. 2020. "The political consequences of opioid overdoses." *PLOS ONE* 15(08): 1–10.

Klar, S., and Y. Krupnikov. 2016. *Independent Politics: How American Disdain for Parties Leads to Political Inaction*. Cambridge University Press.

Klar, Samara. 2014. "Partisanship in a Social Setting." *American Journal of Political Science* 58(3): 687–704.

Lazarsfeld, Paul Félix, Bernard Berelson, and H Gaudet. 1948. *The people's choice: how the voter makes up his mind in a presidential campaign.* New York: Columbia University Press.

Lee, Amber Hye-Yon. 2021. "How the Politicization of Everyday Activities Affects the Public Sphere: The Effects of Partisan Stereotypes on Cross-Cutting Interactions." *Political Communication* 38(5): 499–518.

Legros, Sophie, and Beniamino Cislaghi. 2019. "Mapping the Social-Norms Literature: An Overview of Reviews." *Perspectives on psychological science : a journal of the Association for Psychological Science* p. 1745691619866455.

Levendusky, M. 2009. *The Partisan Sort: How Liberals Became Democrats and Conservatives Became Republicans*. Chicago Studies in American Politics University of Chicago Press.

Mangum, Maruice. 2013. "The Racial Underpinnings of Party Identification and Political Ideology." *Social Science Quarterly* 94(5): 1222–1244.

Manski, Charles F. 1993. "Identification of Endogenous Social Effects: The Reflection Problem." *The Review of Economic Studies* 60(3): 531–542.

Martin, Gregory J., and Steven W. Webster. 2018. "Does residential sorting explain geographic polarization?" *Political Science Research and Methods* pp. 1–17.

Mummolo, Jonathan, and Clayton Nall. 2017. "Why Partisans Do Not Sort: The Constraints on Political Segregation." *The Journal of Politics* 79(1): 45–59.

Nall, Clayton. 2018. *The Road to Inequality: How the Federal Highway Program Polarized America and Undermined Cities*. Cambridge University Press.

Olson, M. 1965. *The Logic of Collective Action: Public Goods and the Theory of Groups*. Harvard economic studies Harvard University Press.

Openshaw, S. 1983. *Concepts and Techniques in Modern Geography*. Norwich, UK: Geo Books chapter The Modifiable Areal Unit Problem.

Parker, Kim, Juliana Horowitz, Anna Brown, Richard Fry, D'Vera Cohn, and Ruth Ignielnik. 2018. What Unites and Divides Urban, Suburban and Rural Communities. Technical report.

Perez-Truglia, Ricardo. 2017. "Political Conformity: Event-Study Evidence from the United States." *The Review of Economics and Statistics* 100(06).

Perez-Truglia, Ricardo, and Guillermo Cruces. 2017. "Partisan Interactions: Evidence from a Field Experiment in the United States." *Journal of Political Economy* 125(4): 1208–1243.

Porter, Ethan, and Jon C Rogowski. 2018. "Partisanship, Bureaucratic Responsiveness, and Election Administration: Evidence from a Field Experiment." *Journal of Public Administration Research and Theory* 28(05): 602–617.

Putnam, Robert D. 2001. *Bowling Alone: The Collapse and Revival of American Community*. New York: Simon & Schuster.

Putnam, Robert D. 2007. "E Pluribus Unum: Diversity and Community in the Twenty-first Century: The 2006 Johan Skytte Prize Lecture." *Scandinavian Political Studies* 30(2): 137–174.

Rodden, J.A. 2019. *Why Cities Lose: The Deep Roots of the Urban-Rural Political Divide*. Basic Books.

Sands, Melissa L. 2017. "Exposure to Inequality Affects Support for Redistribution." *Proceedings of the National Academy of Sciences* 114(4): 663–668.

Sears, David O., and Carolyn L. Funk. 1999. "Evidence of the Long-Term Persistence of Adults' Political Predispositions." *The Journal of Politics* 61(1): 1–28.

Sussell, Jesse. 2013. "New Support for the Big Sort Hypothesis: An Assessment of Partisan Geographic Sorting in California, 19922010." *PS: Political Science and Politics* 46(4): 768–773.

Trounstine, J. 2018. *Segregation by Design: Local Politics and Inequality in American Cities*. Cambridge University Press.

USPS. 2013. The Untold Story of the ZIP Code. Technical report.

Wray-Lake, Laura, Erin H. Arruda, and David A. Hopkins. 2019. "The Party Goes On: U.S. Young Adults Partisanship and Political Engagement Across Age and Historical Time." *American Politics Research* 47(6): 1358–1375.