Partisan Conversion Through Neighborhood Influence: How Voters Adopt the Partisanship of their Neighbors

November 28, 2022

Abstract

Recent studies show that American neighborhoods have become politically homogeneous, raising concerns about how geographic polarization divides parties and influences voters. But it remains unclear how voters are influenced by the politics of their neighbors. I argue that voters are influenced by local norms when defining their own partisan affiliations, adopting local partisanship. Panel data on 41 million voters from 2008-2020 and an original survey of 24,623 respondents demonstrate that exposure to partisan neighbors increases party switching. These effects are largest for older voters, voters in single-family communities, and voters with more same-race neighbors. Survey data support mechanisms of social influence: voters accurately perceive local partisanship, interact more with partisans they live near, and are more comfortable when their partisanship matches neighbors' political affiliations. Partisanship is thus shaped by where voters live and who they live close to, demonstrating the behavioral consequences of geographic polarization.

Introduction

In the United States, Democrats and Republicans increasingly live around neighbors who share their political preferences and partisan attachments (Rodden, 2019; Brown and Enos, 2021), raising concerns that limited exposure to opposing political ideas in voters' residential lives will influence their political behavior and contribute to partisan divides (Cramer, 2016). Scholars of partisanship, geographic polarization and neighborhood effects predict that voters may be directly influenced by the politics of the people they live near, and that this local partisan exposure may drive partisan conversion – where voters adopt the partisanship of their neighbors and local community members (Berelson, Lazarsfeld, and McPhee, 1954; Huckfeldt and Sprague, 1987; Martin and Webster, 2018). Yet, while much is known about how other components of geography, such as race or class, influence voters (Hopkins, 2010; Wong, 2010; Enos, 2017), less is known about how voters respond to neighborhood partisanship, and whether partisan affiliations are shaped by these local norms.

In this study, I argue that voters are influenced by local partisanship, and this residential exposure produces partisan conversion as voters adopt the politics of their neighbors. 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.

Despite 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), voting (Green et al., 2016; Anoll, 2018), and other behaviors such as littering, church attendance, criminal activity, school enrollment, employment, drug and alcohol use, and wearing masks to prevent the spread of COVID-19 (Cialdini, Reno, and Kallgren, 1990; Case and Katz, 1991; Bobonis and Finan, 2009; Baxter-King et al., 2022). Recent research demonstrates that moving to a new state or county influences voter registration (Cantoni and Pons, 2021), but local influence has not yet been precisely measured. 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. 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, household composition, 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.

Second, with the survey data I measure whether voters are aware of neighbors' partisanship, whether residential partisan exposure corresponds with actual interaction with partisan neighbors, and whether voters are more comfortable with neighbors knowing their partisanship when they live around more neighbors who share their party. 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 10 percentage point ($\sim$ 1 standard deviation) increase in exposure to Democratic or Republican neighbors between presidential elections increases the likelihood of switching to that party by 0.3-2.5 percentage points. Compared to baseline rates of party switching between presidential elections, such exposure changes increase the probability of party switching by 18%-40%.

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, and are more comfortable expressing their partisanship when it matches their neighbors'.

Overall, the results indicate that voters' registration and political 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 voters' political identities, the party to which they are registered, is in part determined by where voters live and who they live near.

The rest of the paper proceeds as follows: First, I describe the theoretical motivation for neighbor-influenced partisan conversion. Second, I describe the voterfile data, the measurement strategy for partisan exposure, and descriptive trends in registration and partisan geography. Third, I detail the empirical strategy for the panel analysis, then present the panel results. Next, I describe the survey data, the survey empirical strategy and present the survey results. I conclude with a discussion of potential mechanisms driving the results, and the broader implications of neighbor effects for political behavior.

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 (Sinclair, 2012). 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, their intake of political information, and the observed behaviors that voters may adopt or be socialized into (Huckfeldt and Sprague, 1987).[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 know 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 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 (Titelman and Lauderdale, 2021), 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

[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).

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.

Local 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), how campaigns mobilize voters (Hersh, 2015), and which primary elections they are allowed to vote in[2]. 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; Lyons, 2017).

[2] Except for California, which switched to a top-two primary format for congressional and state-level elections in 2010, each state in the data has some form of a closed or semi-closed primary system for both political parties, meaning that there are eligibility restrictions based on partisan registration. California presidential primaries are still semi-closed (Democrats) and closed (Republicans).

When Should Local 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 by their local community.

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 (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 Explanations

This theory posits mechanisms of social influence, but mobilization could also perpetuate local homogeneity. Campaigns may target voters to register with their party based on low-level geography (Hersh, 2015). This alternative mechanism would still show that neighborhoods can cause voters to change their partisanship, but with the intervention of another actor. I address this alternative explanation in the analysis, examining results across competitive and uncompetitive House districts, to see if results are mainly apparent where campaign activity is highest.

Additionally, policy changes or other shocks may produce local changes in registration. A political event that is geographically concentrated in its impacts may influence voters living in impacted areas to change parties, thus creating spatially clustered episodes of partisan switching. Such events can influence vote choice (Healy and Malhotra, 2010; Sances, 2017), but do not generally lead to changes in registration, except over longer realignments

(Carmines and Stimson, 1989). Electoral conditions may also play a role in how voters respond to partisan geography. For example, voters may be motivated by strategic reasons to register with one party or the other, through a desire to participate in political primaries. Except for California, which switched to a top-two primary format in 2010, each state in this study has a closed or semi-closed primary system for both political parties, meaning that there are eligibility restrictions based on partisan registration. Voters living in districts dominated by one party may respond to this homogeneity by switching their registration so as to influence the political primary that chooses the likely winner of the general election. I return to both these possibilities in the discussion of the estimation strategy, which compares voters living within Zip Codes, and thus likely have similar exposure to such policies and likely live in the same political jurisdictions, so these institutional considerations are held constant.

Voterfile Data

Data for this study comes from 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 TargetSmart. Pre-2012 data were collected from states. Each file contains data on voter name, residential address, household, age, gender, partisan registration, vote history, and race. TargetSmart identifies voter households using address information and voter names, providing a household-level identifier. Race is recorded in Florida and North Carolina, and is imputed by TargetSmart in the other states based on name and census demographics.[3]

I analyze linked samples across 3 presidential electoral cycles: 2008-2012, 2012-2016, and

[3]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 S6.4, I estimate alternative specifications using the posterior probability of being White from the imputation calculations. The results are consistent in these alternative estimations.

2016-2020. Target Smart identifies voters across time periods by linking individuals based on name, age, residential address, voting history, and other proprietary information. I rely on TargetSmart's linkages for 2012-2020 data, and I link pre-2012 files to the TargetSmart 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. This results in 41,323,306 unique[4] voters across these three periods, with 17,391,433 who did not change residences from 2008-2012[5] (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 (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

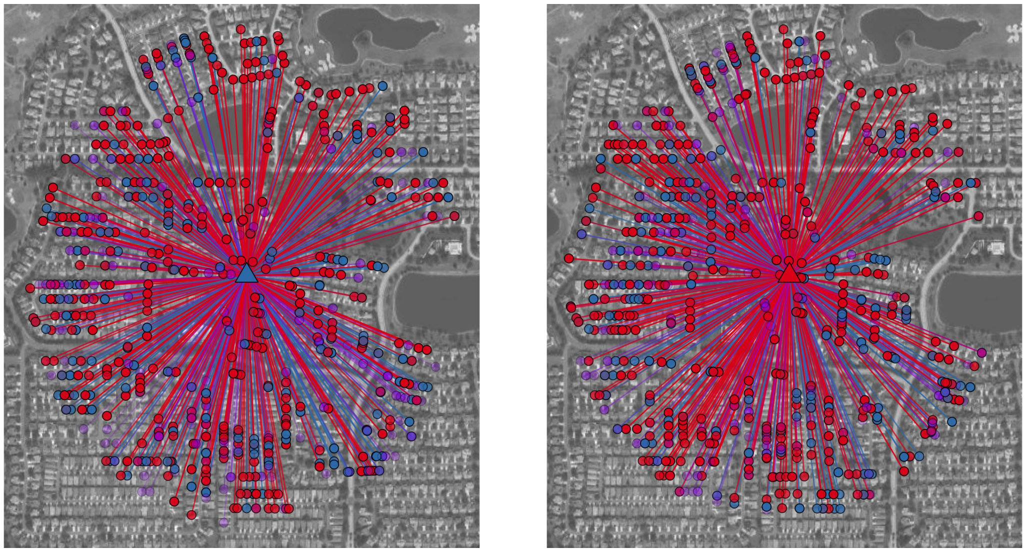
[4]Many voters appear in more than one linked sample, meaning they did not change residences across multiple presidential election cycles.

[5]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.

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. While I find some evidence of differential relocation rates in response to out-partisan neighborhood change, voters do not appear to relocate to neighborhoods with substantially more co-partisans. This pattern is consistent with previous research demonstrating 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. Registrants that are part of the same household as a voter are not included in that voter's exposure calculation. 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[6] 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:

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

These measures differ from those used in (Brown and Enos, 2021) in two ways. First, I do not use imputation to code independents as having a partisan lean. Instead, I measure

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

exposure to *registered* Democrats and Republicans, to avoid measurement error from imputation and because the theory in this paper is about transmission of explicit party affiliation through local geography. Second, I do not include same-household registrants in a voter's neighborhood exposure, but rather measure household composition separately and control for it in the models. Studies that rely on aggregate summaries of exposure generally can not separate household-level and neighborhood-level exposure (Hersh and Ghitza, 2018). But the data in this study measure locations of voters and all the registrants that live around them, so neighbor exposure can be differentiated from household exposure.

In the Supporting Information (Section S6.4) I demonstrate the robustness of the results to other neighborhood definitions and coding decisions, 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 non-partisan neighbors from the denominator – 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 experience across time, with many voters seeing large increases or decreases in exposure.

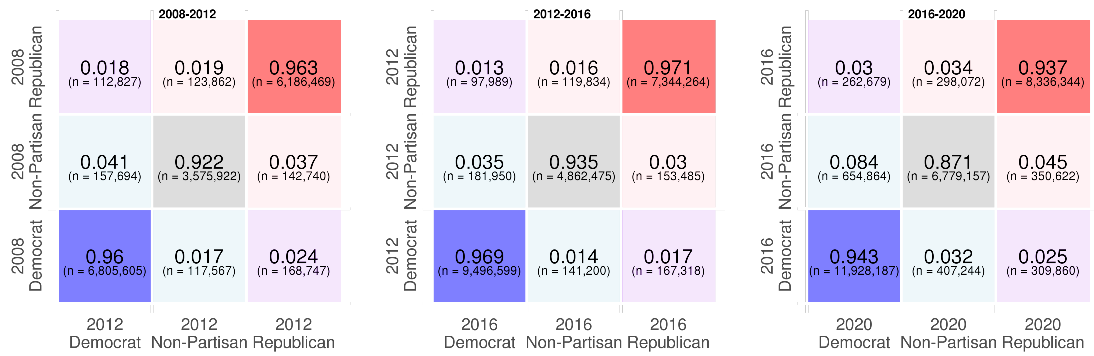


Figure 2: Partisan Transition Matrices

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.

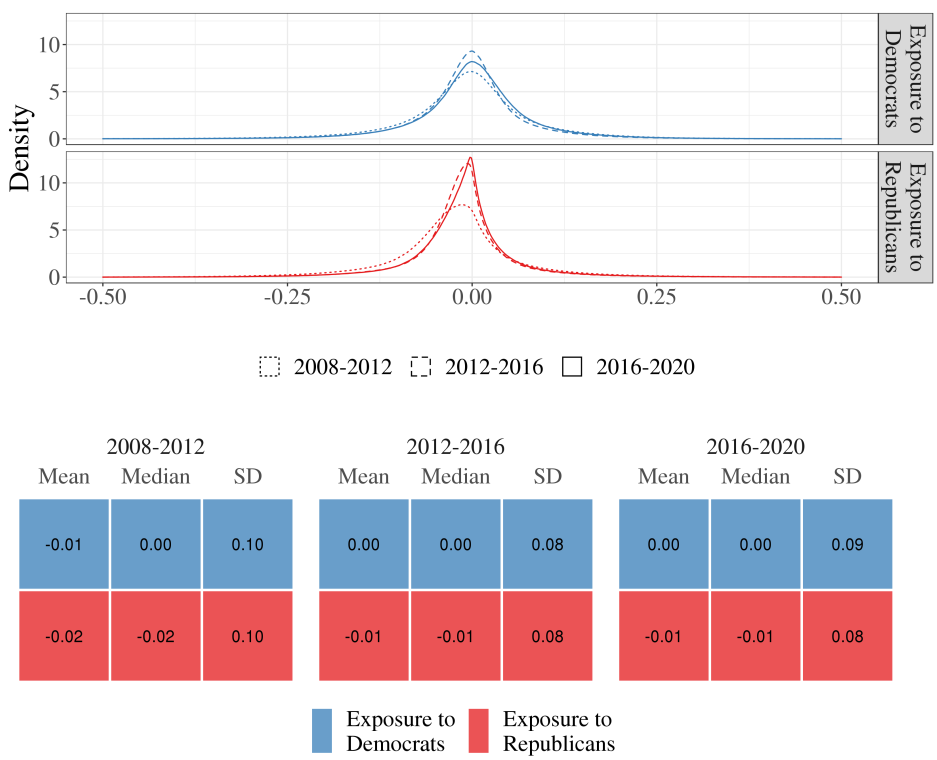


Figure 3: Distribution of Changes in Democratic and Republican Exposure

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. I estimate these effects using a first differences model, measuring the effect of 4-year changes in Democratic or Republican exposure 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, number of Democrats or Republicans in a voter's household, the total number of registrants in a voter's household, and Democratic or Republican exposure decile in the first election year. Using these strata, 75% of voters in the 2008-2012 linked sample, 73% in 2012-2016, and 77% in 2016-2020 have at least one other voter in their matched stratum. 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 (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

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

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, household composition, and starting levels of exposure to Democratic or Republican neighbors.

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. Each model also controls for the change in the number of Democrats or Republicans that live with a voter, and the change in the total number of registrants in a voter's household. Therefore, I am estimating the effect of partisan neighbors net of the effects of household-level partisan composition.[9] 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.[10]

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, $HHDem_{i,t}$ be the number of Democrats and $HHReg_{i,t}$ the number of registered voters that live in the same household as voter i in election year t, and $\boldsymbol{X}_{i,t}$ denote a vector of

[8] All Block Group controls use 2010 Census definitions. I use 5-year American Community Survey data where the final year is the voterfile data year. For 2020, in order to use 2010 Block groups, I use the 2015-2019 ACS. For 2008, I use the 2006-2010 ACS.

[9] Incorporating household partisan composition into the matching strategy and controlling for household-level changes strengthens the claim 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.

[10] 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.

time-varying Block Group covariates. Let α_M be the strata fixed effect and $\epsilon_{i,c}$ the error term. Since measures of partisan exposure are likely spatially correlated, I cluster standard errors at the county-level, a much larger geographic unit than the level at which exposure is measured. I estimate linear regressions of the form[11]:

$$D_{i,t+1} - D_{i,t} = \alpha_M + \theta(DE_{i,t+1} - DE_{i,t}) + \tau(HHDem_{i,t+1} - HHDem_{i,t}) + \lambda(HHReg_{i,t+1} - HHReg_{i,t}) + \boldsymbol{\beta}(\boldsymbol{X}_{i,t+1} - \boldsymbol{X}_{i,t}) + \epsilon_{i,c} \quad (1)$$

I also estimate the effect of Republican exposure on Republican registration, swapping out $D_{i,t}$, $DE_{i,t}$, and $HHDem_{i,t}$ for $R_{i,t}$, $RE_{i,t}$, and $HHRep_{i,t}$ (Republican partisanship, Republican exposure, and number of Republicans in the voter's household), and using Republican exposure decile and number of household Republicans in election year 1 to define α_M. θ represents the effect of one unit increase in Democratic (Republican) exposure on changes in Democratic (Republican) registration.

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 TargetSmart panel.[12] Pre-trends for the 2016-2020 data come from 4 prior years of TargetSmart 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)).[13]

[11] For the future effects, the specification is the same on the right-hand side, but the outcome is $D_{i,t+2} - D_{i,t+1}$, and the sample is limited to voters who do not change partisan registration during the treatment period.

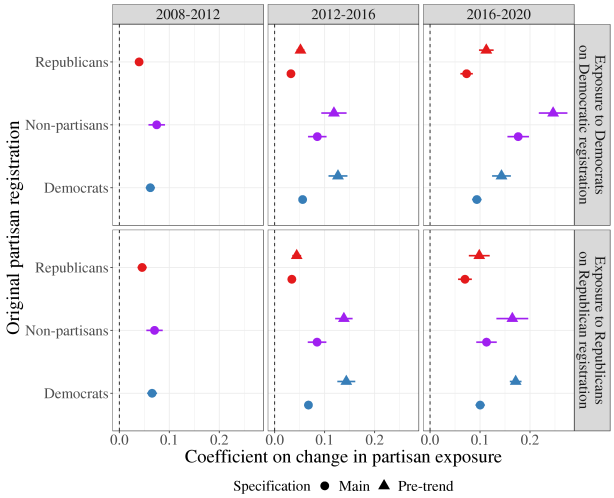
[12] Older voterfile coverage varies by state. California pre-trends are constructed from 3 years of data (2005, 2007, 2009), Florida pre-trends from 2007 and 2009 voterfiles, Kansas from 2008 data, New York from 2001 and 2008 voter records, and North Carolina from 2009 data.

[13] Further discussion of the estimation and identifying assumptions are included in Supporting Information Section S4.

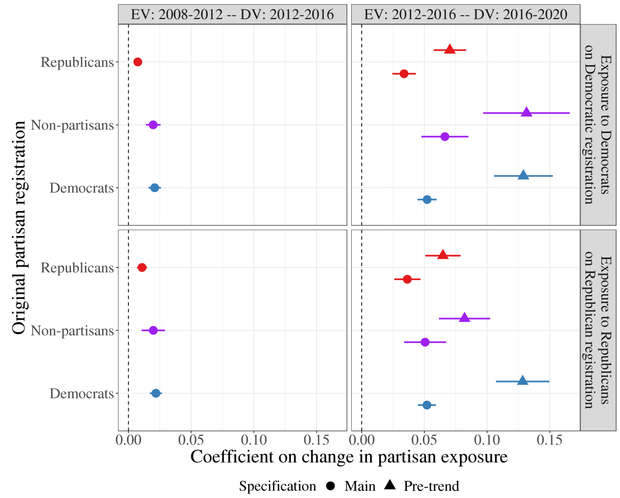
Effect of Partisan Exposure on Partisan Registration

Across election cycles and regardless of original partisanship, voters respond to increases in Democratic (Republican) exposure by becoming more likely to register as Democrats (Republicans). Figure 4 presents the current effect estimates from the main and pre-trend matching specifications, reporting 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 for voters who were originally Democrats is the effect on remaining a Democrat. Likewise, the effect of Republican exposure is the effect on Republican 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. Therefore, the coefficients show that 3% to 25% (depending on year, subset, and specification) of the partisan change among a voter's closest neighbors is translated into that voter's own likelihood of switching party. Another, perhaps 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 0.3-2.5 percentage point increase in the likelihood of registering with that party, depending on model, year and subset. Table S7 in the Supporting information further contextualizes these effects, comparing them to the baseline levels of party switching across years and starting partisanship subsets. Compared to these baseline rates, a 10 percentage point exposure change increases the probability of party switching by 18%-40%.



(a) Current Results



(b) Future Results

Figure 4: Effect 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 results and panel (b) is the future results) 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. Pre-trend specifications were not estimated for the 2008-2012 sample due to pre-trend data availability. Bars plot 95% confidence intervals.

Panel (b) plots the future effects. A 10 percentage point increase in Democratic or Republican exposure from 2008-2012 causes a 0.07-0.2 percentage point increase in switching to that party between 2012-2016, while such an increase from 2012-2016 spurs a 0.3-1.3 percentage point increase in party switching from 2016-2020. Thus changes in partisan exposure produce both contemporary and downstream influences on party registration.

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 each year from 2012-2015. I do so using the main specification, matching individuals on 2016 covariates. Figure 5 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.

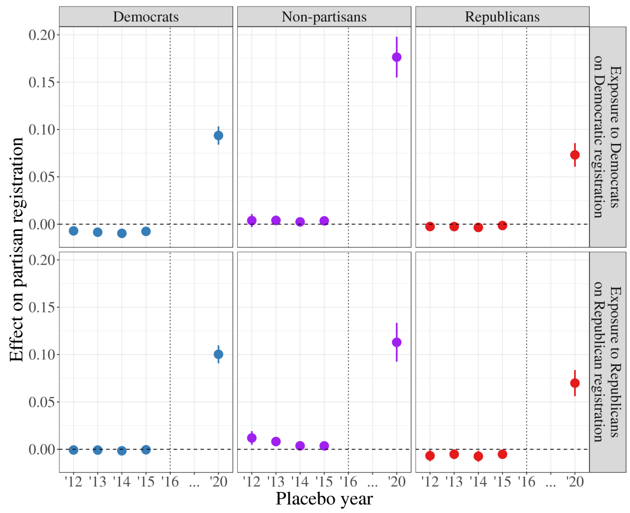


Figure 5: Placebo Trends

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.

Heterogeneous results: age, housing type, neighbor race, and campaign activity

Here, I present results by 1) voter age 2) whether voters live in single-family homes or apartments, 3) whether increased partisan exposure comes from same-race neighbors, and 4) by district competitiveness. The first three subset analyses focus on instances where local influence may be stronger – where voters are potentially more connected to their communities or more likely to interact with neighbors. The last analysis, district competitiveness, tests whether the results appear to be driven by an alternative explanation: campaign activity.

To estimate the age and housing heterogeneous effects, I subset the data by age and housing type and estimate the current effect specifications for the 2012-2016 and 2016-2020 linked samples within subsets. Figure 6 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.[14] The results are larger for voters living in single-family homes, while the effects for voters in apartments are muted. The effects are generally increasing by age (although this trend is more muted for voters originally registered Republican) within the single-family home group, but do not vary substantially by age for voters in apartments.

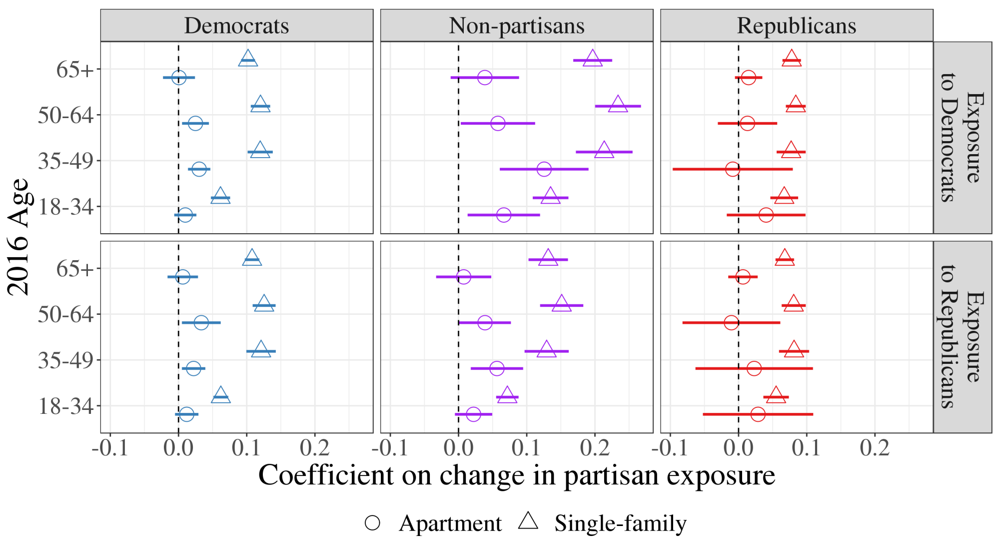


Figure 6: Effect of Partisan Exposure by Age and Housing Type

Figure plots effect of a one unit (100 percentage point) increase in Democratic exposure on Democratic partisanship (top row) and effect of a similar increase in Republican exposure on Republican partisanship (bottom row) for the 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

[14]The 2012-2016 results produce similar patterns and are shown in the Supporting Information Figure S2.

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 effect for ingroup voters should be larger than for outgroup voters. The other three specifications are similar in structure, but with partisan exposure operationalized by exposure to Black, Asian, and Hispanic neighbors, respectively, with the corresponding interaction term for that race.[15]

Figure 7 plots the effects from these models for the 2016-2020 linked sample.[16] Exposure to White partisans generally has the largest effects for White voters, compared to non-White voters. The results for Asians (and exposure to Asian partisans) and Hispanics (and exposure to Hispanic partisans) mirror those for Whites, but the effect of Black partisan exposure for

[15] 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.

[16] The 2012-2016 results are shown in the Supporting Information Figure S4.

Blacks is generally statistically indistinguishable from that for Non-Blacks.

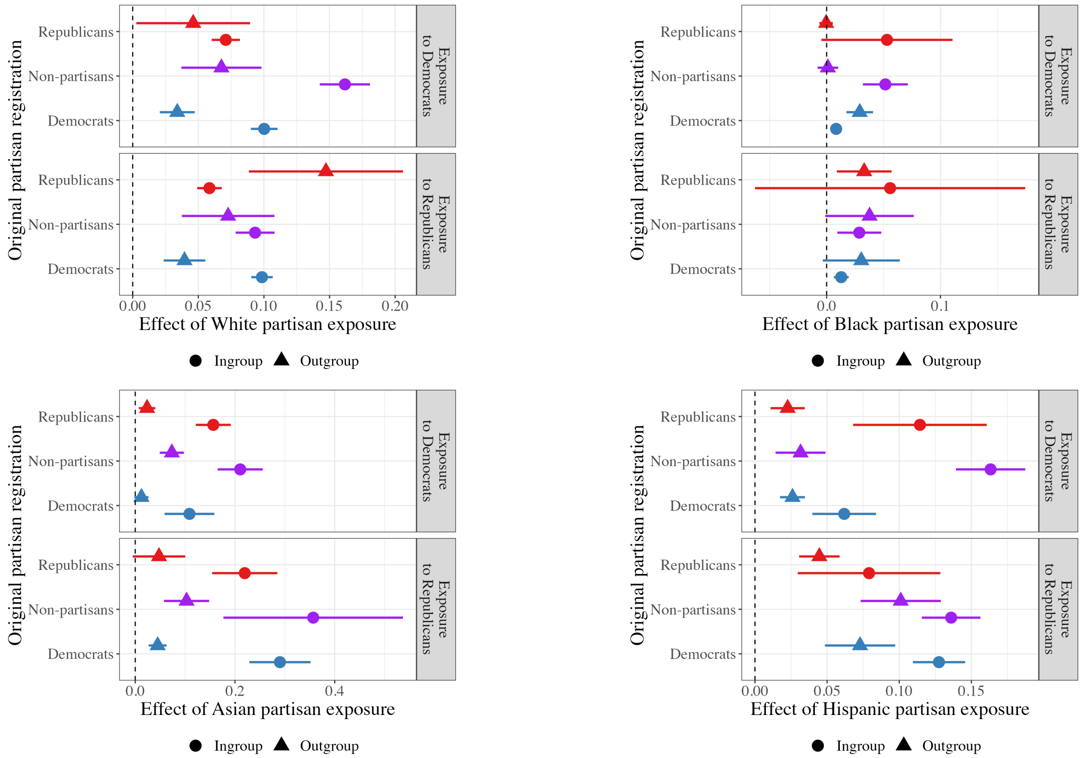


Figure 7: Voters are Most Influenced by Same-Race Neighbors

Top left figure plots effect of exposure to White Democrats or White Republicans, from the current effect specifications for the 2016-2020 linked sample. Points are plotted separately for in-group and out-group voters. The other figures plot the same coefficients, but from models interacting whether a voter is Asian, Black, or Hispanic (bottom left, top right, bottom right) and partisan exposure from neighbors of that race. Bars plot 95% confidence intervals.

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).

Next, I present the results by district competitiveness. If campaign activity is driving the effects then results should be larger in competitive electoral districts, and potentially

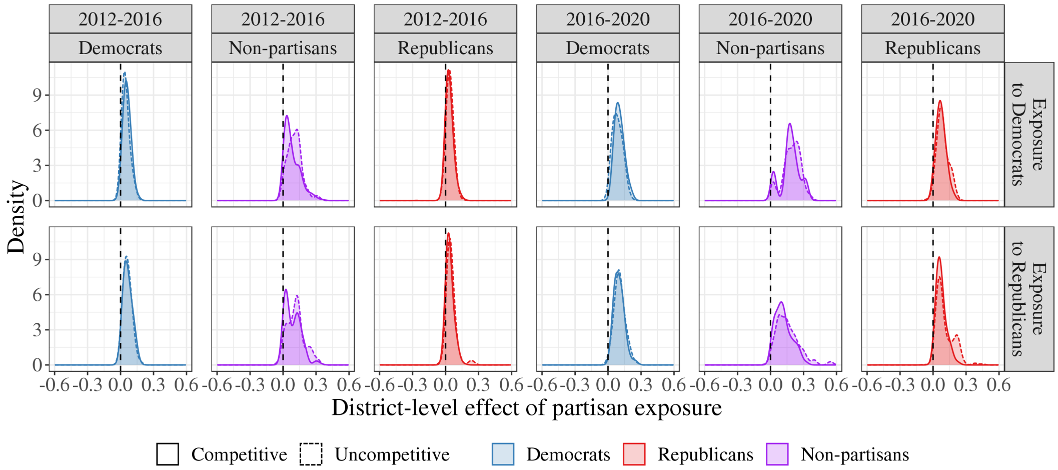


Figure 8: District Electoral Competition is not Determinant of Effect Size

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

non-existent in uncompetitive ones. To test this, I subset the 2012-2016 and 2016-2020 linked samples by House district, and re-estimate the main specification within these district subsets. I then classify each district as uncompetitive if across the time period the same party represented the district, and the minimum margin of victory never fell below 20 percentage points. Figure 8 shows the distribution of these district-level estimates across districts, weighting by sample size in each district, plotting separate histograms for competitive and uncompetitive districts. Not only do the results persist in uncompetitive districts but the distributions for competitive and uncompetitive districts almost entirely overlap, indicating that electoral competition is not determinant of effect size.

Survey Evidence of Local 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 whether voters are aware of the partisanship of their neighbors, how partisan demographics shape neighbor interaction, 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. 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, and they feel social discomfort if they are politically different from local norms.

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 TargetSmart. 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 1.59%, 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

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)
Neighbors know voter's party	Very uncomfortable – Very comfortable (1 - 5)

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.

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.

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.[17] I also include terms for the number of Democrats

[17] Details on the construction of the weights, and the results without weights, are provided in the Supporting Information (Section S7).

or Republicans in the survey respondent's household in 2020, and a term for the number of total registrants in the household. 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 effects. I estimate regressions of the form:

$$Y_i = \theta DE_i + \tau HHDem_i + \lambda HHReg_i + \boldsymbol{\beta X}_i + \gamma_z + \epsilon_{i,c} \tag{2}$$

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. θ represents the increase in the survey outcome corresponding to a 100 percentage point increase in Democratic or Republican exposure.

Survey Results

Table 2 presents the neighbor exposure results from the models[18] 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 3-4 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.

[18] 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.

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

	Neighbors: Democrats or Republicans		Contact: Democrats	Contact: Republicans	Comfort: Neighbors know Party	
	(1)	(2)	(3)	(4)	(5)	(6)
Dem Exp	1.24		0.76		-0.10	
	(0.14)		(0.34)		(0.23)	
Dem Exp * Dem					0.62	
					(0.27)	
Rep Exp		-1.20		1.59		-0.34
		(0.13)		(0.29)		(0.23)
Rep Exp * Rep						0.93
						(0.31)
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	0.600	0.599	0.407	0.469	0.440	0.444
R^2 Adj.	0.511	0.509	0.267	0.344	0.274	0.279
Covars	✓	✓	✓	✓	✓	✓
FE: Zip Code	✓	✓	✓	✓	✓	✓

Table presents results from WLS regressions 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 (100 percentage point) increase in exposure. Standard errors clustered at the county level are shown in parentheses.

In Models 5-6, I interact[19] 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 survey results demonstrate that variation in partisan geography describes meaningful

[19] Models 5-6

$$\begin{aligned} Y_i = \theta DE_i + \rho D_i \times DE_i + \tau HHDem_i + \omega D_i \times HHDem_i + \\ \lambda HHReg_i + \kappa D_i \times HHReg_i + \boldsymbol{\beta} \boldsymbol{X}_i + \boldsymbol{\eta} D_i \times \boldsymbol{X}_i + \gamma_z + \epsilon_{i,c} \end{aligned}$$

variation in political context for voters, influencing how they perceive their neighborhood, the rate at which they interact with members of each party, and their comfort expressing their own partisanship. As such, the results illustrate the sequence by which partisan exposure may be internalized by voters, shaping partisan interaction, and activating social pressure, which collectively may influence voters assessment of their own partisan affiliations.

Conclusion

This paper provides evidence on a key piece of missing information on how voters are influenced by local geography: 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. Residential exposure to partisans 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'. 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.

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. 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. The effect of a one standard deviation increase in partisan exposure makes voters 0.3-2.5 percentage points more likely to adopt the party of their neighbors, an 18%-40% increase over the baseline probability of switching party. This represents a large relative increase in party switching, and this partisan conversion has substantive implications given the sometimes razor-thin electoral margins between partisan candidates. Further, the effect sizes 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.

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 consider their own partisanship. Furthermore, while exposure may 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 Trump's America." *The ANNALS of the American Academy of Political and Social Science* 681(1): 137–156.

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): 494–508.

Baxter-King, Ryan, Jacob R. Brown, Ryan D. Enos, Arash Naeim, and Lynn Vavreck. 2022. "How local partisan context conditions prosocial behaviors: Mask wearing during COVID-19." *Proceedings of the National Academy of Sciences* 119(21): e2116311119.

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* .

Carmines, Edward G, and James A Stimson. 1989. *Issue Evolution: Race and the Transformation of American Politics*. Princeton, N.J.: Princeton University Press.

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.

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.

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* .

Healy, Andrew, and Neil Malhotra. 2010. “Random Events, Economic Losses, and Retrospective Voting: Implications for Democratic Competence.” *Quarterly Journal of Political Science* 5(2): 193–208.

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.

Hersh, Eitan D., and Yair D. Ghitza. 2018. “Mixed partisan households and electoral participation in the United States.” *PLOS ONE* 13.

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. 2010. “Politicized Places: Explaining Where and When Immigrants Provoke Local Opposition.” *American Political Science Review* 104(1): 40–60.

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.

Imai, Kosuke, and Kabir Khanna. 2016. “Improving Ecological Inference by Predicting Individual Ethnicity from Voter Registration Records.” *Political Analysis* 24(2): 263–272.

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.

Lyons, Jeffrey. 2017. "The Family and Partisan Socialization in Red and Blue America." *Political Psychology* 38(2): 297–312.

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

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.

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).

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. 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.

Sances, Michael W. 2017. “Attribution Errors in Federalist Systems: When Voters Punish the President for Local Tax Increases.” *The Journal of Politics* 79(4): 1286–1301.

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.

Sinclair, Betsy. 2012. *The Social Citizen: Peer Networks and Political Behavior*. Chicago Studies in American Politics University of Chicago Press.

Titelman, Noam, and Benjamin E. Lauderdale. 2021. “Can citizens guess how other citizens voted based on demographic characteristics?” *Political Science Research and Methods* p. 1–21.

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

Wong, Cara. 2010. *Boundaries of Obligation in American Politics: Geographic, National, and Racial Communities*. New York: Cambridge University Press.

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.