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

Jacob R. Brown†

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Abstract

Recent studies find that many American neighborhoods have become politically homogeneous, raising concerns about how geographic polarization divides parties and influences voters. What drives this pattern? I argue that voters are influenced by their neighbors' politics, adopting the partisanship of people they live near. I test this using individual-level panel data on over 41 million voters from 2008 to 2020, and an original survey of over 24,000 respondents linked to voterfiles. Focusing on voters who do not move between elections, I find that exposure to partisan neighbors increases the likelihood of switching registration to match neighbors' partisanship. These 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 neighborhood partisanship, interact more with partisans they live near, and view Democrats or Republicans more favorably when they have more neighbors from that party. These results demonstrate that partisanship is shaped by where voters live, and this conversion reinforces ongoing processes of political segregation.

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†Institute for Quantitative Social Science and Department of Government, Harvard University, Email: jrbrown@g.harvard.edu, Website: https://jacobrbrown.com

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). This local political homogeneity creates electoral imbalances that threaten fair representation (Rodden, 2019; Chen and Rodden, 2013), erode support for regional policies such as transit and infrastructure (Nall, 2018; Trounstine, 2018), and provoke concerns that living in isolated communities exacerbates differences between polarized political parties (Cramer, 2016). Given these trends, it is important to understand what is causing increasing geographic homogeneity, as well as how living in partisan neighborhoods influences voters.

Most of local partisan homogeneity is due to sorting by characteristics associated with politics, such as race or class (Rodden, 2019), and the alignment of partisanship with these geographically clustered demographics (Levendusky, 2009). On top of this, there are two channels through which politics may directly influence partisan sorting. First, through *separation* – Democrats and Republicans 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 a portion of partisan homogeneity, *conversion*, where voters adopt the partisanship of those they live near.

In this study, I argue that voters are influenced by the partisanship of their neighbors, and this residential partisan exposure produces a process of partisan conversion that reinforces patterns of local homogenization. As neighborhoods become more Democratic or Republican voters take in information about changing partisan norms in their community, interact more 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 Democratic or Republican neighbors will be influenced to change their partisan registration to match. For voters whose registration already matches local trends, more co-partisan neighbors will make it more likely that they remain a member of that party.

While there is limited prior evidence linking local context to partisanship, controlled experiments and observational research alike demonstrate that voters are influenced by neighborhood norms, adopting the behaviors of those they live near, when making political donations (Perez-Truglia, 2017; Perez-Truglia and Cruces, 2017), voting (Gerber, Green, and Larimer, 2008; 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 political attitudes and behavior (Putnam, 2007; Enos, 2017; Sands, 2017). As neighborhoods become more 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 the relationship between local geography and political behavior face persistent measurement and design challenges. Precise data on where voters live in relation to each other is difficult to obtain, and most measures of geographic exposure are limited to aggregate summaries of local 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 to 2020. These data document nearly every registered voter in these states during these time periods, recording for each year of the panel the residential address and partisan registration of each voter. I supplement these panel data with an original survey of over 24,000 voters from the panel.

With these data, I conduct two analyses. First, I measure the effect of changing exposure to Democratic and Republican neighbors on voters' 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 precise 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 their neighbors' partisanship, and the relationship between voters' local partisan exposure and interaction with partisan neighbors, comfort with neighbors knowing their partisanship, perceptions of the ideology of both political parties, and feelings of warmth towards Democrats and Republicans. Collectively, these analyses test the hypotheses that voters are responsive to the political norms of their local environment and that changes in these norms influence partisan attitudes and registration.

The data show that increased residential exposure to Democrats or Republicans makes voters more likely to switch their registration to match their neighbors' partisanship. 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 Democratic or Republican exposure from neighbors who are the same race as them. The survey data further show that voters accurately report the partisanship of their neighbors, 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 their 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), the data demonstrate that sizable numbers of voters do switch their partisan registration. For these voters, the partisan context in which they live is a potentially important input affecting this switch. These findings show that political group membership is 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 ongoing processes of geographic polarization. As neighborhoods and communities become more politically homogenous, voters will increasingly change their registration to match local trends, exacerbating political isolation and the (geographic) distance between the parties.

Partisan Conversion through Neighborhood Influence

While partisanship is often characterized as a social identity (Green, Palmquist, and Schickler, 2004) it is also malleable, sensitive to factors that may result in 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 less direct contexts may also have effects. These less direct contexts, such as one's neighborhood, 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 will follow these norms, adopting the group membership and behaviors of those around them. As neighborhoods grow more Democratic or more 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' neighbors are structures who they come in contact with in their residential lives and informs the observed behaviors that voters may adopt or be socialized into (Cutler, 2007).[1] Voters may infer partisan norms from direct cues such as conversations with neighbors, political yard signs, bumper stickers, local media, and targeted campaign messages, or from indirect cues such as neighbors' cars, jobs, whether they are religious, what products they buy, what music they listen to, and other seemingly apolitical lifestyle choices from which voters infer partisan orientations (Lee, 2020). This knowledge of descriptive norms creates perceptions of social pressure or rewards (Legros and Cislaghi, 2019) that may push voters to re-evaluate their own partisan affiliations. This could be the perception of community judgement for opposing beliefs or may be internal, a sense of utility that comes from feeling similar to one's local community.

This process does not require that voters have extensive relationships with their 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 of their neighbors, and 44% say they

[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).

communicate with neighbors on a weekly basis. For these voters the socializing influence of neighborhoods may flow through interpersonal contact. But neighborhoods can still exert important influences even on voters with limited direct contact with their neighbors. Conversations with neighbors are just one of many informational cues from which voters infer partisan norms (Lee, 2020), so even voters who do not frequently interact with their neighbors likely have an accurate sense of the partisanship of their neighborhood, and still may respond to the social pressure that comes from knowledge of descriptive norms.

Additionally, geographic 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 stereotypical caricatures of hyper-partisans, potentially from images from national media (Ahler and Sood, 2018). But as one has more neighbors from that political party, a new image may emerge for what it means to be a Democrat or Republican, and voters may reconsider their own registration within this new frame.

Social Influence on Partisan Registration

Partisan conversion in this model happens through changes in partisan registration. Registration is both reflective of partisan preference and an important political outcome on its own, structuring how politicians and bureaucracies view constituents (Porter and Rogowski, 2018), how districts are drawn (Chen and Rodden, 2013), and how voters are mobilized into politics (Hersh, 2015). Registration has also been shown to have downstream influence on partisan attitudes, strengthening ties to the party one is registered to (Gerber, Huber, and Washington, 2010).

I anticipate that changes in local partisan context produce changes in registration primarily by altering the social pressures, norms, and strategic calculations that govern the translation of partisan preference into partisan affiliation. Changes in underlying partisan preferences in response to exposure to new political ideas from neighbors may also be occurring, but the process of changing attitudes, and then translating these new attitudes into new partisan affiliations, is a slow process. Shifts in partisan preferences mainly occur in response to long-term socialization or major policy shifts by the political parties (Campbell et al., 1960; Carmines and Stimson, 1989). In general, social pressure and neighborhood norm adoption better explain changes in explicit behavior or group membership than attitude change (Druckman and Green, 2013).

Alternative Explanations and Expectations

This theory posits mechanisms of neighborhood influence, but these patterns could be driven by political institutions reacting to changes in local partisan geography. First, 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 retrospective voting has been shown to influence vote choice, as voters frequently reward or punish incumbents based on performance or other socio-economic events (Fiorina, 1981; Healy and Malhotra, 2010; Sances, 2017), although these effects generally do not extend to changes in actual 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.

Alternative models also offer competing predictions for how voters should respond to local partisan demographics. 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.

Data and Measurement

Studies connecting political behavior to geography usually must rely on aggregate summaries of geographic variables and behavioral data, and are thus impeded by measurement error common to ecological inference (White, 1983; Openshaw, 1983). With such data it also is difficult to connect geography to behavior with claims to causality, as absent temporal variation or natural population shocks researchers must make likely implausible identifying assumptions. For this study, testing whether neighbors influence each other's partisanship requires fine-grained measures of partisan exposure and individual-level partisanship across multiple time periods. With this in mind, I construct a panel of linked voter records across 5 states covering 2008 to 2020, with even longer panels in some states. These data contain information on each voter's residential address and partisan registration for each year during which a voter was registered. This information allows for individual-specific measures of partisan geography, measuring each voter's exposure to Democratic and Republican neighbors. I then track individuals over time as their partisan geography changes, connecting these changes to changes in registration. I supplement these data with an original survey of voters from the panel, collecting outcomes on voters' awareness of local partisan geography, interactions with partisan neighbors, and perceptions of members of each political party.

Panel of Voters

To construct the panel, I use linked voter records from California, Florida, Kansas, North Carolina, and New York. These states were selected based on the ability to construct panels reaching back to 2008, offer a variety of regional and political contexts, and encompass 27% of the U.S. electorate and 48% of registered voters living in states that record partisanship. Table S1 in the Supporting Information details the data coverage. All voter data from 2012 to 2020 were provided by the vendor Target Smart. All files prior to 2012 were collected from states. For the main analysis, I analyze linked samples across 3 presidential electoral cycles: 2008-2012, 2012-2016, and 2016-2020. Each file contains data on voter's name, residential address, age, gender, partisan registration, vote history, and race. Each voter's residential address is geocoded so that the data contain the latitude and longitude coordinates of the each voter's residence. Race is recorded in Florida and North Carolina, and is imputed in the other states based on a name and census demographics.

In the analysis, I focus on voters who do not changes residences between elections, but rather see their neighborhoods change around them. 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 their registration (see Cho, Gimpel, and Hui (2019)). For example, focusing on non-movers rules out confounding biases that comes from material differences in 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 this bias-creating dynamic would be if Democratic or Republican 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. 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).

Target Smart links voters across time periods using state information and by linking individuals based on name, age, residential address, and vote history. I rely on Target Smart linkages in my analysis of panels starting in 2012 or later, 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 that uses exact matching to avoid false positives, which would inflate the rate of partisan switching. This results in 41,323,306 unique[2] voters across these three election cycles, with 17,391,433 voters who did not change residences from 2008-2012[3] (39% of 2008 registrants),

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

[3]I do not have 2008 voterfiles for each state. To construct the 2008-2012 linked sample, I use the California

22,565,114 voters from 2012-2016 (49% of 2012 registrants), and 29,327,029 voters from 2016-2020 (59% of 2016 registrants). The unlinked voting population either moved, de-registered, or failed to link[4]. Some of the differences in proportion linked across years are due to residential mobility decreasing across the time period – in 2008 12.5% of people reported moving in the past year, down to 9.3% in 2020 (CPS, 2020). Projected across 4-year periods, the linkage rates reflect these rates of mobility. Full details of the linking process are provided in the Supporting Information (Section S1).

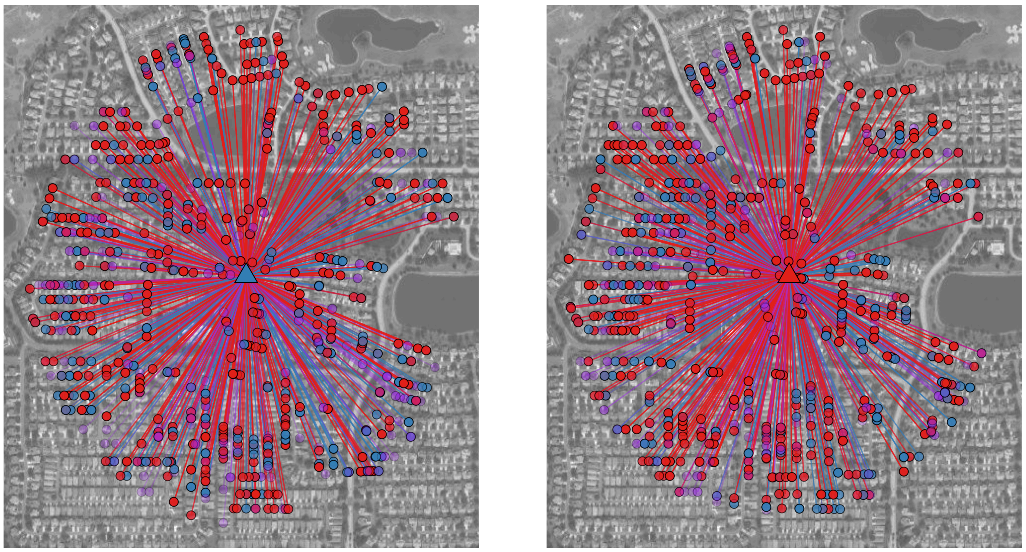
Measuring Partisan Context

Normally, measures of exposure rely on aggregate summaries from areal units, assuming that every person living in a unit has same level of exposure. But two voters living in even the same neighborhood can have different levels of exposure to Democrats and Republicans among their closest neighbors (Brown and Enos, 2021). Testing the influence of neighbors is best served by measures of partisan geography that can take into account where voters live in relation to each of their neighbors. The voter file data contain the geolocated residential addresses of every voter and their registered neighbors. With this information, I measure partisan exposure by constructing *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 the neighbors who live closest to each voter when calculating their exposure to Democrats or Republicans. Figure 1 illustrates this process, plotting the 1,000 most proximate neighbors for a Democrat in Wildwood, FL

2007, Florida 2007, Kansas 2008, New York 2008, and North Carolina 2009 voterfiles.

[4]This linking process determines which voters are included in the main analysis. It does not determine which voters are included in calculations of partisan exposure in each year. For those calculations the entire registered population in the states are used.

who switched to Republican after a large increase in their exposure to Republicans from 2016 to 2020. While the overall balance of the voter's 1,000 nearest neighbors shifts Republican, the most noticeable shift is the neighbors who live closest to the voter. This highlights the importance of weighting by proximity to capture the voter's change in partisan exposure.



2016 2020

Figure 1: Partisan Exposure Maps

Maps plot the nearest registered neighbors at the latitude and longitude coordinates of each voter's residential address. Democrats are colored blue, Republicans red, and non-partisans purple. The voter saw a large (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 the 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, $D_{i,j,t}$ be the distance[5] in meters between voter i and neighbor j in year t, and $Y_{j,t}$ be the partisan registration of neighbor j in year t. Partisan exposure is defined as:

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

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

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

This measure offers several advantages. First, it is unique to each voter, calculating exposure with each voter at the center of their 'neighborhood', and thus better capturing the individual residential experience of each voter. Second, this measure uses information on the distance a voter lives from each of their neighbors to give greater weight to more proximate neighbors. This feature of the measurement is important for testing the influence of neighbors, since it is these closest neighbors who should have the largest influence. 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 possible measurement error in imputing partisan preference for voters not registered to a major political party. This measure is also limited in that it cannot account for unregistered neighbors, but I include controls for Census Block Group proportion registered (calculated from combining voterfile registration counts with Census population data) in the estimation to account for the influence of changes in the density of registered voters.

In the Supporting Information (Section S6.4) I demonstrate the robustness to other neighborhood definitions, including aspatial measures of exposure (1,000 nearest neighbors without accounting for distance between neighbors), neighborhoods defined by 100 and 500 nearest neighbors, neighborhoods defined by neighbors within one mile and half a mile from the voter, and by Census Block and Census Block Group. The results are also consistent when dropping same household neighbors, and when dropping non-partisan neighbors – operationalizing treatment as exposure to Democrats or Republicans out of total partisan neighbors.

Registration and Partisan Exposure Trends in the Linked Samples

Next, I present the trends in registration and partisan exposure in each of the linked samples. Voters in the linked samples exhibit high levels of partisan stability. Figure 2 plots the partisan transition matrices across presidential elections. Just 5.7% of voters in 2008, 2012, and 2016 are registered to a different party 4 years later. In the Supporting Information Table S5, I present descriptive statistics of voters across stable partisans and partisan switchers.

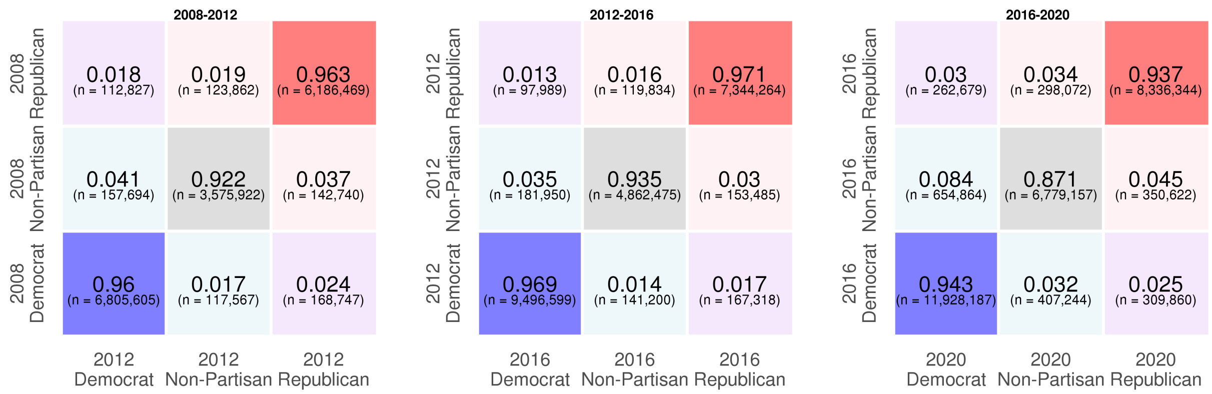


Figure 2: Partisan Transition Matrices

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

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 significant variation in the types of neighborhood changes that voters experience across time, with many voters seeing large increases or decreases in exposure. In the Supporting Information Table S6, I present descriptive statistics of voters and neighborhoods across different levels of change in partisan exposure.

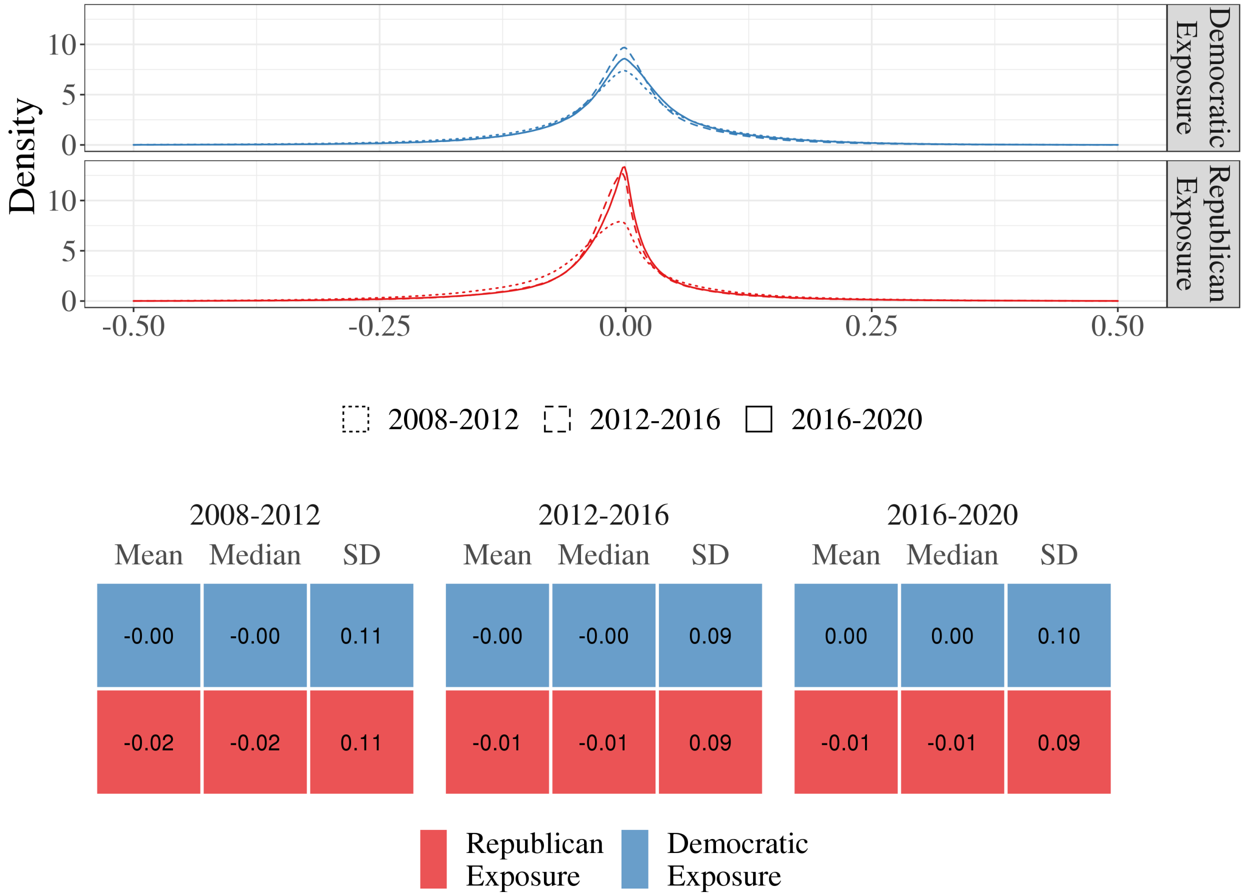


Figure 3: Distribution of Changes in Democratic and Republican Exposure

Figure plots the distribution of within-individual changes in exposure to Democratic (blue) and Republican (red) neighbors across time periods for all voters who did not change residences 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.

Survey Data

The panel data described above are designed to measure the causal relationship between residential partisan exposure and partisanship, but are limited in their capacity to inform as to why voters may respond to neighborhood changes with changes in their own partisanship. Therefore, I combine the panel data with an original cross-sectional survey of voters with responses linked to voterfiles, collecting a richer set of data on voter attitudes that can be linked to local partisan context. This survey is part of a large nationwide survey designed to test the relationship between geography and political attitudes, but includes specific modules to support the idea that voters are responsive to the politics of their neighbors. These modules include perceptions of the ideology of each political party, feelings of warmth towards Democrats and Republicans, perceptions of neighborhood partisan composition, levels of interaction with Democratic and Republican neighbors, and levels of comfort with neighbors knowing one's partisanship. The survey was administered via e-mails using e-mail addresses linked to voter records by Target Smart. Since voters are surveyed directly off the voterfile, I connect survey responses to voters' residential addresses, and thus to the individual measures of partisan exposure described in previous sections.

Table 1 reports the survey outcomes used in the main analysis, and the scales of each outcome. To measure geographic perceptions, the survey asks respondents whether the people in their neighborhood 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 scale from "None/not at all" to "A great deal". 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". Perceptions of party ideology are measured on a 7 point scale from "Very conservative" to "Very liberal". Favorability towards each party is measured through feeling thermometers where respondents rate their favorability towards Democrats and Republicans on a 0 to 100 scale. The survey also contains demographic questions, information on respondents' partisanship, strength of partisanship, and ideology.

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)

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. 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 1.48%, similar to single-digit response rates typically seen in phone or email surveys. Since the data are intended to support the panel findings on partisan registration, I limit the survey analysis to respondents who are in the 2016-2020 linked panel data and who verified their identity in the survey, leaving a sample of 24,623 voters. Full details of survey administration are provided in the Supporting Information (Section S7.1), as are summary statistics comparing the survey sample to the registered voting population. In the analysis I incorporate survey weights designed to make the sample more representative of the electorate.

Research Design

With these data, I conduct two analyses. First, I use the panel data to to measure the effect of changing exposure to Democratic and Republican neighbors on individual 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 of partisan conversion:

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

With the survey data, I measure the relationship between local partisan exposure and perceptions of neighborhood partisanship, interaction with partisan neighbors, comfort with neighbors knowing one's partisanship, perception of Democratic and Republican party ideological extremity, and feelings of favorability towards Democrats and Republicans. Through this survey analysis, I test the following hypotheses:

Perceptions of Neighborhood Partisanship: Voters who live in more Democratic (Republican) neighborhoods report that more of their neighbors are Democrats (Republicans).

Contact with Partisan Neighbors: Voters who live in more Democratic (Republican) neighborhoods report more frequent interpersonal contact with Democratic (Republican) neighbors.

Partisan Social Pressure: Voters whose partisan registration matches their neighbors' will be more comfortable with their neighbors knowing their partisanship.

Partisan Ideological Extremity: Voters who live in more Democratic (Republican) neighborhoods report that the Democratic (Republican) party is less ideologically extreme.

Partisan Favorability: Voters who live in more Democratic (Republican) neighborhoods report greater favorability towards Democrats (Republicans).

Panel Estimation

To test the central hypothesis, I compare within-voter changes in partisan registration across voters who experience different changes in partisan context during the time periods of study. 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 from 2008 to 2012, 2012 to 2016, and 2016 to 2020. The treatment is the change in Democratic or Republican exposure from the first election year to the second. The outcome is the change in Democratic or Republican registration.

To better isolate the effect of partisan 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 aggregate characteristics. I also subset my analysis by political party in the first election year, so I am estimating effects separately for subsets defined by original partisan registration. This combination of Zip Code and individual covariates strata provides a powerful comparison, matching voters who live in the same small geography and are similar along other characteristics, so any change in registration in response to different changes in partisan exposure after accounting for these similarities are likely the result of neighbor influence. For example, this estimation strategy should capture the influence of localized political shocks that might produce spatially clustered partisan switching and overall changes in neighborhood composition, since most shocks are not operating within Zip Code and within the other individual characteristics used to create the strata. This includes features such as how primary rules or the competitiveness of a voter's district influence strategic motivations for partisan conformity, since voters living in the same Zip Code generally will be subject to the same electoral jurisdictions. Similarly, restricting the comparison to voters living in the same Zip Code accounts for the selection process that led to voters living in this same small geography.

To account for other contextual trends likely correlated with local partisan exposure and changes in voter partisanship, I control for changes in Block Group[6] level income, employment, racial demographics, the median age of the population, housing values, proportion homeowner, 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. Block group is the smallest Census geography where these variables are available. 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.[7]

I estimate the following first differences model: 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 ϵ_i the error term. I estimate regressions of the form:

[6] I used the 5-year American Community Survey Block group data where the final year is the voterfile data year. For 2020 Census data is not yet available, so I use the 2019 estimate. For 2008, I use the 2006-2010 ACS data, which provides the data using 2010 census Block Group definitions.

[7] 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. The older state files also do not have marital status, so that variable is not used for the 2008-2012 sample.

$$D_{i,2} - D_{i,1} = \alpha_M + \theta(DE_{i,2} - \mathrm{DE}_{i,1}) + \boldsymbol{\beta}(\boldsymbol{X}_{i,2} - \boldsymbol{X}_{i,1}) + \epsilon_i \qquad (1)$$

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 rather than Democratic exposure decile to define α_M. θ represents the effect of a one unit increase in Democratic (Republican) exposure on changes in individual Democratic (Republican) registration from election year 1 to election year 2. All models use cluster-robust standard errors clustered at the county-level.

Identifying Assumptions

There are several threats to inference that must be considered in order to interpret these estimates causally. First, many things besides the partisanship of voters' neighbors could have changed in their local area during the time periods of study. 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 in the analysis to better address the parallel trends assumption.

First, I incorporate individual and contextual variables in the data to narrow the scope of my comparison to compare most similar individuals. I do this through the inclusion of the matched covariate strata in the main specification, comparing individuals who are of the same original partisanship, race, gender, marital status, are of similar ages, live in the same Zip Code, and live in similar types of neighborhoods in terms of partisan exposure. Using these strata, over 90% of voters in each linked sample have at least one other voter in their matched stratum. Table S4 in the Supporting Information demonstrates that there is variation in changes in exposure within strata, with an average within-strata standard deviation change in Democratic and Republican exposure of approximately 0.06.

I also estimate an alternative specification designed to account for pre-trends, dropping the covariate matching strata and instead creating strata defined by partisan registration and coarsened (rounded to the nearest percentage point) levels of 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[8]. Pre-trends for the 2016-2020 data come from 4 prior years of Target Smart data (2012-2015). This specification is thus restricted to voters who also 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 to better ensure that the parallel trends assumption holds (for example, see Hall and Yoder (2021)).

The parallel trends assumption in this case is complicated by the fact that the outcome and the treatment are both measuring partisan registration. A voter who switches registration will influence the treatment of a different voter to whom they are a neighbor. In a neighborhood where many voters are changing their registration for reasons that are unrelated to neighbor influence, it may still appear that this switching happens in response

[8]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.

to neighbors. However, these factors would have to produce spatially clustered groups of partisan switchers independent from the individual and aggregate characteristics already accounted for in the main specification, or from the treatment and outcome trends accounted for in the pre-trend specification. Still, in the Supporting Information (Section S6.4) I conduct two analyses to test the sensitivity of the results to this concern. First, I estimate a specification that controls directly for the net number of neighbors who switch their registration to Democrat or Republican, thus estimating the effect of changes in partisan exposure holding constant the level of partisan switching among neighbors. Second, I estimate a specification that operationalizes changes in neighborhood exposure based only on inflows and outflows of new neighbors. The substantive interpretation of the results are consistent in both specifications.

Survey Estimation

With the survey data, I model the relationship between Democratic and Republican exposure on perceptions of neighborhood partisanship, levels of contact with Democratic and Republican neighbors, perceptions of how liberal or conservative the Democratic and Republican parties are, and feelings of favorability towards Democrats and Republicans. The overarching goal of the estimation is to test for relationships between local partisan exposure and these survey outcomes, particularly when accounting for a host of individual and aggregate variables, and making low-level geographic comparisons, to account for many of the factors that may confound the influence of partisan exposure. The key explanatory variable in this case is the change in Democratic or Republican exposure from 2016 to 2020. In the estimation, I control for 2016 levels of Democratic or Republican exposure, so the coefficient on the 2016 to 2020 change represents the predictive effect of the 4-year change in partisan exposure conditional on the starting levels. I use weighted least squares regressions, weighting by survey weights[9], controlling for individual (respondent 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. I also include Zip Code fixed effects. I estimate regressions of the form:

$$Y_i = \theta(\mathrm{DE}_{i,2020} - \mathrm{DE}_{i,2016}) + \tau\mathrm{DE}_{i,2016} + \boldsymbol{\beta X}_i + \gamma_z + \epsilon_i \tag{2}$$

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.

Results

Effect of Neighborhood Partisan Exposure on Partisan Registration

The panel analysis reveals a consistent relationship between changes in residential exposure to Democrat and Republican neighbors and voters' partisan registration. Figure 4 presents the estimates from the main and pre-trend matching specifications, plotting the effect of increasing 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 increase 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 of switching registration to Democrat across the time period. The effect of Democratic exposure on Democratic partisanship for voters who

[9] 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.

were originally Democrats is the effect on the likelihood of 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 a Republican for voters who were originally Republicans.

Across election cycles and regardless of original partisan registration, increases in the number of Democrats (Republicans) among a voter's 1,000 nearest neighbors increases the likelihood of registering as a Democrat (Republican). The coefficients in Figure 4 represent the effect associated with a 100 percentage point increase in partisan exposure, 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 between a 20% to 60% increase over the baseline probability of changing partisan registration.

The magnitude of these effects can be compared to previous research on changes in partisanship, which finds single digit effects on partisanship or partisan registration across many different explanatory variables and experimental interventions, including voter outreach (Gerber, Huber, and Washington, 2010), early-life exposure to racial diversity (Brown et al., 2021), major life events such as marriage, divorce or retirement (Hobbs, 2019), family drug-related deaths (Kaufman and Hersh, 2020), and historical events (Hersh, 2013). These studies show that partisan registration is responsive to a host of political outcomes, but effects are consistently small. In this context, the estimates represent reasonable yet meaningful effect magnitudes. Moreover, across millions of voters and across multiple time periods, these effects likely produce substantial shifts in partisan registration.

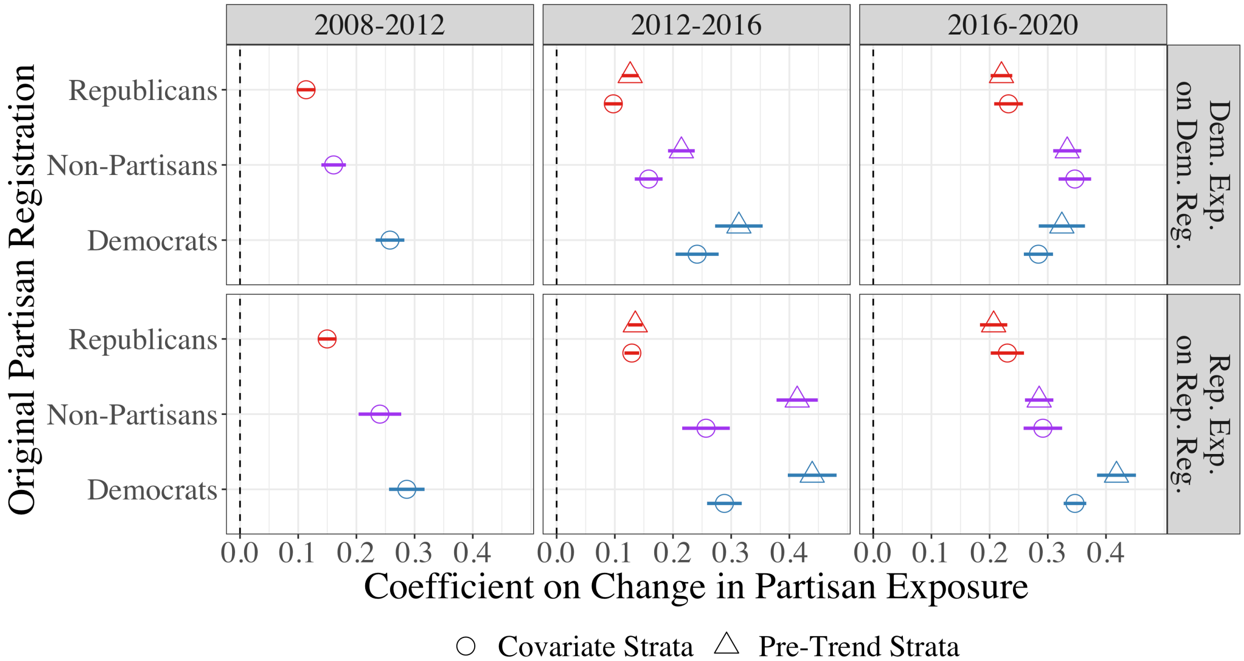


Figure 4: Effect of Partisan Exposure on Partisan Registration

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), separately for the 2008-2012 (left column), 2012-2016 (middle column), and 2016-2020 (right column) linked samples. 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.

The pre-trends strata specifications return similar estimates as the main specifications. As an additional test of the identifying 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 5 plots the effects on the placebo outcomes. With this estimation strategy, changes in partisan exposure from 2016-2020 are not predictive of past trends in partisanship, with these coefficients close to zero.

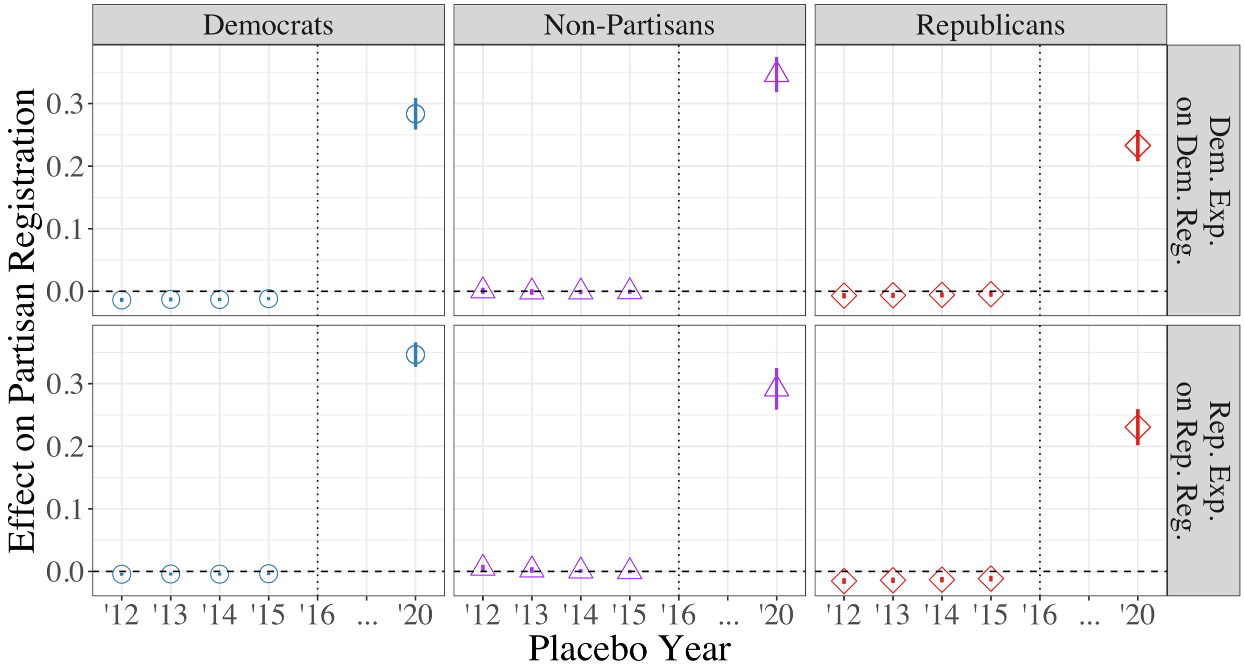


Figure 5: Placebo Trends

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). Where the point is plotted along the X-axis corresponds with which 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 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.

The robustness of the results are further tested in the Supporting Information (Section S6), where I show them to be consistent across alternative time periods and within individual states. I also test whether changes in partisans exposure produce downstream changes in registration, estimating the effect of 2012 to 2016 changes in partisan exposure on voters changing their registration in the following 4-year period, 2016-2020. I find that voters who see an increase in Democratic or Republican exposure but do not change registration by 2016 still become more likely to switch partisan registration in the next four years after the initial increase. I also examine non-linearity in the effect of partisan exposure on partisan registration, finding that the marginal effect of an increase in partisan exposure is increasing with changes in that exposure, meaning that voters are most persuaded to shift their registration in respond to larger changes, whereas small changes seem to have negligible effects.

Lastly, I estimate results separately by U.S. House district, to assess the alternative mechanism of campaign mobilization. If campaign activity is primarily the effects, then results should be substantially larger in competitive electoral districts, and potentially non-existent in uncompetitive ones. 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. These results are shown in Figure S2 in the Supporting Information.

Partisan Influence is Largest for Voters Most Likely to be Connected to their Neighborhoods

If the effect of changes in neighborhood partisan exposure is a feature of interpersonal influence, then I expect the effects to be largest in contexts where neighborhood norms are most likely to be transmitted and adopted. To test this, I examine heterogeneous results by 1) voter age 2) whether voters live in single-family communities or apartments, and 3) whether increased partisan exposure comes from same-race neighbors. Older voters report knowing more of their neighbors than younger voters, and this relationship is steadily increasing with age (Parker et al., 2018). Therefore, older voters may be more likely to be influenced by their neighborhood shifting Democratic or Republican, whereas younger voters may be less influenced by their local geographic network, potentially due to greater residential transience or greater influence from competing social networks including online networks. Voters living in single-family communities may more readily observe their neighbors and interact with them compared to voters living in high-rise apartment buildings, 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. Research in sociology and psychology argues that living in high-density cities is associated with reduced neighborhood ties (Fischer, 1982), and urban residents report lower levels of trust in their neighbors than rural or suburban residents (Parker et al., 2018). Lastly, voters may be most influenced by neighbors who are similar to them along other characteristics. 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 likely to adopt partisan cues.

To measure how effects vary across age and housing type, I subset the data by these variables, and estimate the main 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. 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 substantially larger for voters living in single-family homes, while the effects for those living 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 living in apartments. The effects for 2012-2016 are similar, and are shown in Supporting Information Section S6.7, as are the results subset to Whites only, to show that the heterogenous pattern are not due to differences in race across age groups or housing type.

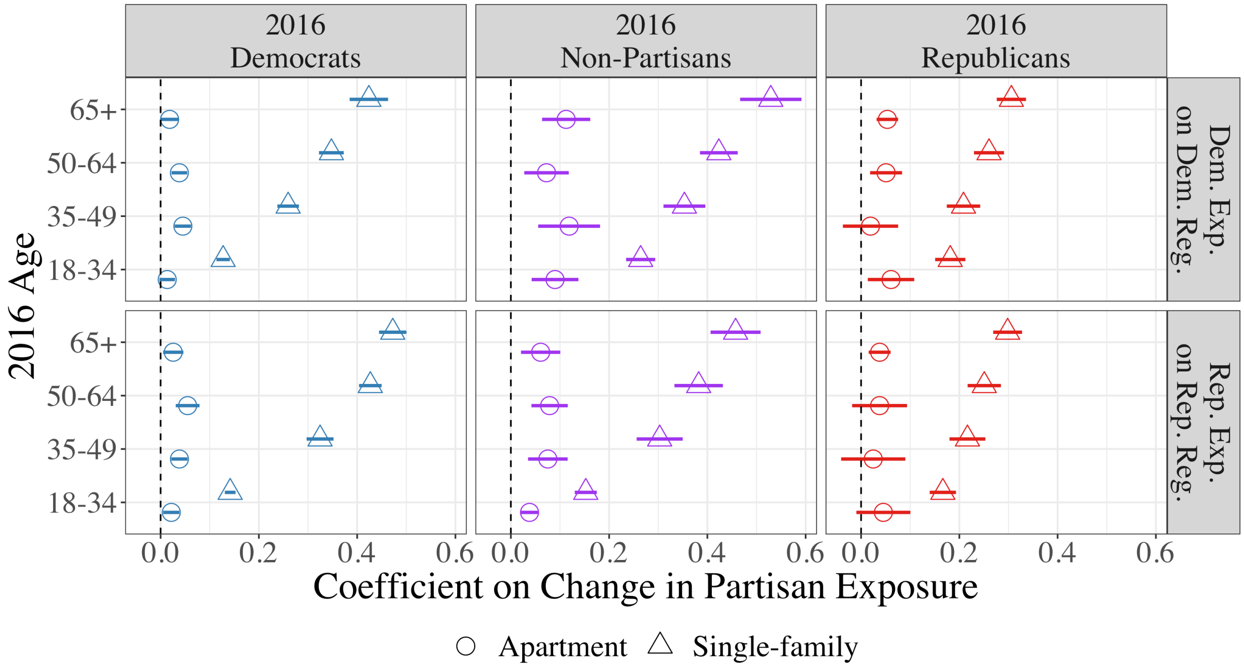


Figure 6: Effect of Partisan Exposure by Age and Housing Type

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 2016-2020 linked sample. 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.

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 the proportion of each voter's 1,000 nearest neighbors who are White Democrats or White Republicans 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 coefficient on the interaction of White and change in partisan exposure should be positive, i.e. White voters should experience the largest effect on partisanship from White neighbors. The other three specifications are similar in structure, but with partisan exposure operationalized by exposure to Black, Asian, and Hispanic partisan neighbors, 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 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 7 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. In general, these results indicate that voters are most influenced by their neighbors' partisanship when their neighbors are similar to them along other dimensions, which is consistent with neighbor influence driving the registration effects.

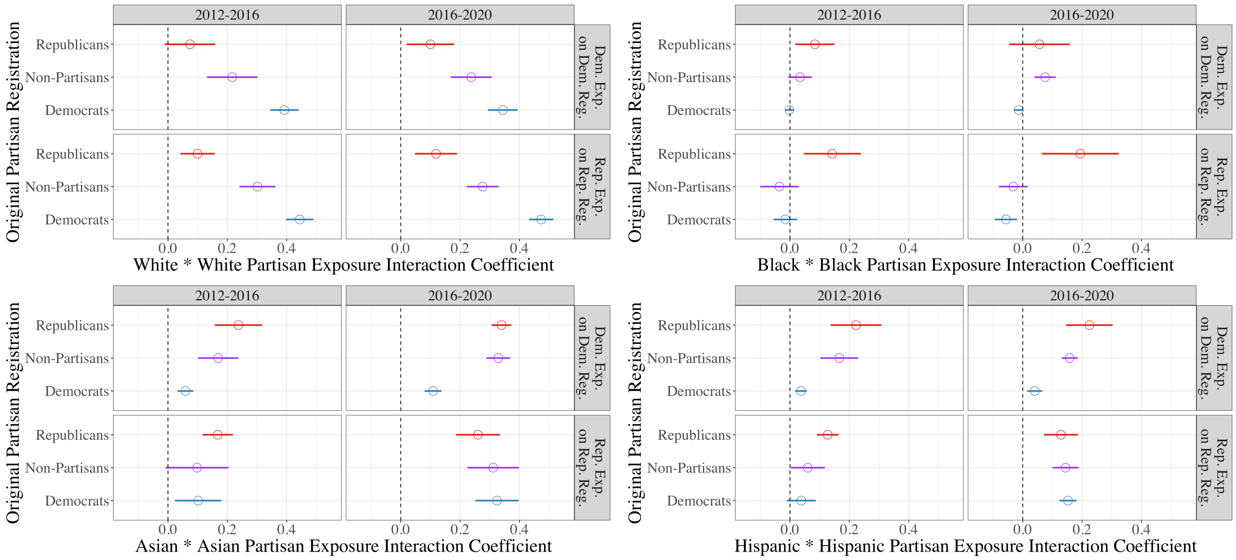


Figure 7: Voters are Most Influenced by Same-Race Neighbors

Top left figure plots the coefficient for the interaction between whether a voter is White and exposure to White Democrats or White Republicans. 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.

Survey Results

The panel data provide evidence in support of the central hypothesis, that increasing partisan exposure drives partisan conversion. To test the remaining hypotheses, I present results from the survey analysis. Comparing voters who live in the same Zip Code, and accounting for individual traits and other characteristics of voter neighborhoods, I find a persistent relationship between partisan exposure and voters' perceptions of their neighborhoods, contact with partisan neighbors, comfort sharing their partisanship, and views of both political parties.

The raw correlation between Democratic exposure and Republican exposure and the perception of neighborhood partisanship survey question is 0.44 and -0.43, respectively, so voters perceptions of neighborhood partisanship are strongly associated with objective partisan exposure before accounting for any confounders. Table 2 presents the results from the models[10] for perceptions of neighbors' partisanship, interaction with partisan neighbors, and comfort sharing partisanship with neighbors. The coefficient on the change in Democratic exposure in Model 1 is positive and significant, meaning that increased Democratic exposure from 2016 to 2020 predicts reporting that one's neighborhood is more Democratic than Republican. This means that voters whose neighborhoods became more Democratic over the past four years perceive their neighbors as being more likely to be Democrats, even conditioning on how Democratic their neighborhood already was in 2016. The coefficient on Democratic exposure in 2016 is also positive indicating that at baseline living in more Democratic areas, regardless of recent trends, is associated with reporting more of one's neighbors as Democrats, further consistent with voters having accurate perceptions of their local partisan context. The the coefficients in Model 2 on change in Republican exposure and 2016 Republican exposure are negative, meaning that both recent trends and 2016 levels of Republican exposure are associated with reporting more Republican neighbors.

Models 3 and 4 demonstrate that there is a positive relationship between change in Democratic exposure and contact with Democratic neighbors as well as a positive relationship between 2016 levels of Democratic exposure and contact with Democratic neighbors. Thus, voters who live in more Democratic neighborhoods interact more with Democratic neighbors, and those that saw a recent increase in Democratic neighbors interact more with Democrats even conditional on starting levels. There is an even larger association between change in Republican exposure and 2016 Republican exposure and contact with Republican neighbors. Thus, exposure to partisan neighbors is predictive of not only how voters perceive

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

the partisan makeup of their neighbors, but further associated with their level of contact with Democratic or Republican neighbors. These associations demonstrate relationships – awareness of partisan context and interaction with partisan neighbors – that should exist for residential exposure to influence partisanship. That these associations are robust to accounting for numerous individual and aggregate variables and looking within small geographies to compare voters similar in their residential location further supports the theory of partisan conversion being driven by neighborhood influence.

In Models 5 and 6, I interact[11] Democratic and Republican registration with change in Democratic and Republican exposure as well as 2016 levels, respectively, to see if there are differential effects by registration of partisan exposure on comfort with one's neighbors knowing one's partisanship. For Model 5, the coefficients related to the 4-year change in Democratic exposure are not statistically distinguishable from zero, so contemporary changes do not appear to have a predictive effect. The coefficient for 2016 Democratic exposure is significant and negative, meaning that non-Democrats become less comfortable with the idea of their neighbors knowing their partisanship when they live around more Democratic neighbors. The interaction coefficient for 2016 Democratic exposure and Democratic partisanship is significant and positive, meaning that Democrats see an increase in their comfort sharing their partisanship when they live around more Democratic neighbors. Model 6 reports the same coefficients but for Republican exposure interacted with Republican partisanship. In this model, only the interaction coefficient between 2016 Republican exposure and Republican partisanship is significant, and its positive magnitude means that Republicans see a larger increase than non-Republicans (who see no increase) in their comfort sharing their partisanship with their neighbors when their Republican exposure is higher. This means that

[11]Models 5 and 6 are in the form:

$$\begin{aligned}Y_i = {} & \theta(DE_{i,2020} - DE_{i,2016}) + \lambda DE_{i,2016} + \tau D_i \times (DE_{i,2020} - DE_{i,2016}) + \\ & \delta D_i \times DE_{i,2016} + \boldsymbol{\beta X}_i + \boldsymbol{\eta} D_i \times \boldsymbol{X}_i + \gamma_z + \epsilon_i\end{aligned}$$

while recent trends in partisan exposure do not predict Democrats or Republicans being more or less comfortable expressing their partisanship to their neighbors, overall Democrats and Republicans living around more co-partisan neighbors are more comfortable sharing their partisanship, providing some evidence that voters are sensitive to the social pressure that comes from the partisan norms of their local environment.

Next, I present results that test the relationship between partisan exposure and perceptions of party ideology and favorability towards Democrats and Republicans. I anticipate that as voters come into contact with more Democrats or Republicans in their local environments, they will come to view the parties as less ideologically extreme, as local examples supplant nationalized stereotypes, and adopt more positive perceptions of party members. These attitudinal shifts may inform the registration decisions observed in the panel analysis.

Table 4 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 in 2016 describe the Democratic Party as less liberal compared to those with less exposure to Democrats. Further, conditional on the 2016 levels, those who saw a 4-year increase in Democratic exposure rate Democrats as even less ideologically extreme. This pattern is not observed, however, in Model 2 estimating how Republican exposure predicts ideological assessments of the Republican Party. The coefficients on 2016 levels and the 2016-2020 change are not statistically distinguishable from zero. Models 3 and 4 measure the relationship between exposure and feelings of favorability towards partisans. Democratic exposure and change in exposure are both strongly predictive of positive favorability of Democrats, and Republican exposure and recent change in exposure is similarly predictive of Republican favorability. Thus, voters who live around more Democrats may think the Democratic Party is less ideologically extreme, and view Democrats more favorably, than those who live with fewer Democratic neighbors. Voters who live around Republican neighbors do not necessarily change their perception of Republican party ideology, but nonetheless

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)
Δ Democratic Exposure '16-'20	0.57		0.74		-0.33	
	(0.17)		(0.32)		(0.24)	
Democratic Exposure '16	0.56		0.64		-0.42	
	(0.11)		(0.22)		(0.18)	
Δ Democratic Exposure '16-'20 * Democrat					0.34	
					(0.37)	
Democratic Exposure '16 * Democrat					0.74	
					(0.22)	
Δ Republican Exposure '16-'20		-0.45		0.89		0.05
		(0.14)		(0.31)		(0.31)
Republican Exposure '16		-0.67		1.29		0.02
		(0.11)		(0.21)		(0.22)
Δ Republican Exposure '16-'20 * Republican						0.44
						(0.40)
Republican Exposure '16 * Republican						0.61
						(0.24)
Mean Outcome	3.83	3.83	3.44	3.55	4.05	4.05
Number of Observations	18,956	18,956	17,983	17,997	14,232	14,232
R^2	0.585	0.585	0.388	0.444	0.422	0.426
R^2 Adj.	0.493	0.494	0.246	0.315	0.253	0.258
Covariates	✓	✓	✓	✓	✓	✓
Fixed Effects: Zip Code	✓	✓	✓	✓	✓	✓

Table presents the results from weighted least squares 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.

Table 4: Partisan Exposure on Party Ideology and Partisan Favorability

	Dem Ideo	Rep Ideo	Dem Therm	Rep Therm
	(1)	(2)	(3)	(4)
Δ Democratic Exposure '16-'20	-0.35		21.64	
	(0.14)		(3.63)	
Democratic Exposure '16	-0.42		16.43	
	(0.11)		(2.42)	
Δ Republican Exposure '16-'20		-0.15		15.93
		(0.19)		(3.32)
Republican Exposure '16		0.21		10.37
		(0.13)		(2.35)
Mean Outcome	5.86	2.14	49.28	45.97
Number of Observations	20,980	20,965	18,720	18,686
R^2	0.513	0.431	0.718	0.709
R^2 Adj.	0.415	0.317	0.655	0.644
Covariates	✓	✓	✓	✓
Fixed Effects: Zip Code	✓	✓	✓	✓

Table presents the results from weighted least squares 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.

still express greater favorability towards Republicans.

Overall, 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. The isolated predictive effect of exposure on each of the outcomes are small, but that they survive at all in this restrictive comparison suggests that voters are responsive to their neighbors' partisanship, and this context influences their partisan attitudes.

Conclusion

Drawing on multiple data sources and novel measures of local partisan context, I present new evidence that voters are influenced by the politics of their neighbors. As voters' neighborhoods change around them, they become more likely to align their partisan registration with those of their neighbors. These effects are apparent across multiple elections, and can be observed across different states and larger political contexts. The effects also exist regardless of the past partisanship of the voter. The influence of neighbors is largest for voters who are more likely to feel connected to and interact with their neighbors: older voters, voters living in single-family homes, and voters whose partisan exposure comes from neighbors of the same race as them. These results are further supported by survey evidence showing an enduring relationship between partisan context and voters' perceptions of neighborhoods, interaction with partisans, political expression, and opinion of the political parties. Together, these findings point to a model of partisan conversion wherein voters observe shifting partisan norms in their local environment and are influenced to switch their registration to match.

These results extend scholarship on how political geography influences political attitudes and behaviors. Voters' political affiliations are influenced by the affiliations of their neighbors, highlighting the role of local political context in shaping partisan attitudes and the translation of those attitudes into registration and political expression. These contextual effects also have broader consequences for the trajectory of partisan segregation in the U.S., in that they may exacerbate ongoing processes of partisan sorting that are making neighborhoods politically homogeneous. A neighborhood sees an influx of new out-partisan voters, and neighborhood residents are influenced to change their partisanship. As some of these voters change, this further shifts the partisan norms in the area, influencing more voters to consider converting to the partisan majority. Thus even small socializing effects on voters can have snowballing effects, with decidedly large consequences for geographic polarization.

There are limitations to this analysis that should be considered. First, the analysis can only speak to the effect of local context on registration, since partisanship in this study is measured through registration data. Likewise, partisan context is measured through exposure to registered partisan neighbors. Many neighbors who are either not registered or not registered to a major party may still have a partisan preference, and may influence their neighbors to adopt this preference. Therefore, the analysis may miss the extent of the socializing influence of neighbors on partisanship. Second, the survey data present only cross-sectional evidence of attitudinal relationships that are consistent with voters being responsive to their local geography. Without temporal variation or exogenous leverage over local partisan context it is difficult to make causal inferences from the survey data. These limitations present opportunities for future work to further test the theories tested in this analysis, and to better investigate the mechanisms by which partisan neighborhoods influence voters.

To some, these results may signal deepening divisions between U.S. political parties. As neighborhoods polarize, partisan conversion increases, heightening geographic divisions. This may drive parties to be disproportionately representative of certain geographic interests, and may limit the exposure of voters to competing political ideas. But from a different perspective, these results point to the potential for non-political commonalities to supersede nationalized partisan polarization. When neighborhoods change, and voters are influenced to adopt neighbors' partisanship, they are putting aside perceived partisan differences. These marginal partisans are likely not ideologically or affectively extreme, so it does not necessarily follow that this geographic conversion is leading to polarization on other dimensions. Further, it is possible that the contextual causes of partisan conversion could help to reverse segregation trends: if neighborhoods start to trend towards integration, voters may respond to these changes by switching their partisanship back and hastening that process.

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