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

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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 the people they live near. I argue that voters are influenced by the partisanship of their neighbors when defining their own partisan affiliations, adopting local partisanship. Panel data on over 41 million voters from 2008-2020 and an original survey of 24,623 respondents demonstrate that exposure to partisan neighbors increases the likelihood of switching registration to match local partisanship. 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; Oliver, 2010; Enos, 2017; Sands, 2017; Hankinson, 2018), 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; Perez-Truglia and Cruces, 2017), voting (Green et al., 2016; Anoll, 2018), and other behaviors such as littering, church attendance, criminal activity, school enrollment, employment, 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. 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, 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 to further support these causal inferences.

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. Since just 5.7% of voters change their party registration between presidential elections, these effects constitute a 5%-40% increase over baseline probabilities of changing party. 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 (Mutz and Mondak, 2006; 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 knowing most, and 44% say they communicate weekly with neighbors. For these voters the socializing influence of neighborhoods may flow through interpersonal contact. But neighborhoods can still exert influence on voters with limited 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 national media (Ahler and Sood, 2018). But with more neighbors from a political party,

[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).

new images may emerge for what it means to be Democratic or Republican, and voters may reconsider their own registration within this new frame.

Social Influence on Partisan Registration

Conversion in this model happens through changes in partisan registration. Registration is reflective of partisan preference and an important political outcome itself, structuring how politicians view constituents (Porter and Rogowski, 2018), how districts are drawn (Chen and Rodden, 2013), 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).

Alternative Expectations

Alternative models offer competing predictions for how voters should respond to local partisanship. Some scholars point to the decline of neighborhoods as social institutions in

[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).

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

Voterfile Data

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

I construct the panel using voterfiles from California, Florida, Kansas, North Carolina, and New York. These states offer varied regional and political contexts and encompass 27% of the U.S. electorate and 48% of voters living in states that record partisanship. All voter data from 2012-2020 were provided by the vendor 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 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

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

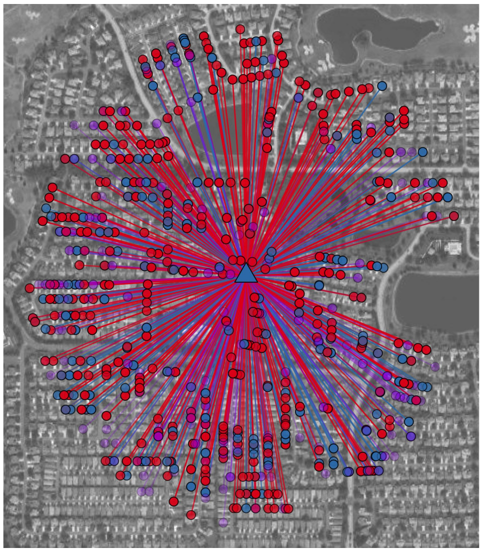
[4] Many voters appear in more than one linked sample, meaning they did not change residences across multiple presidential election cycles.

[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.

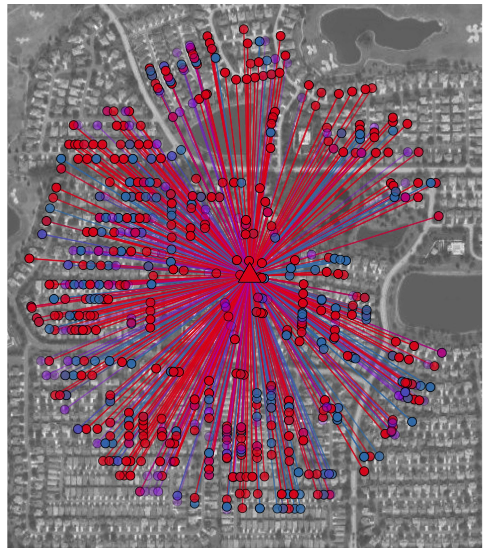
on non-movers holds constant material differences between neighborhoods, such as moving to a wealthier neighborhood with higher property taxes. But this strategy does not completely solve selection issues. If the process that causes someone to stay in a neighborhood is the same process that causes someone to change their partisanship, then the results may be biased. One pattern that would be consistent with such bias would be if voters are more likely to move to a more co-partisan neighborhood in response to out-partisan change in their current neighborhood. In the Supporting Information (Section S2), I analyze mobility patterns for voters who change residences across the panel. 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:

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

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

In the Supporting Information (Section S6.3) I demonstrate the robustness of the results to other neighborhood definitions, including not accounting for distance between neighbors, neighborhoods defined by 100 and 500 nearest neighbors, by neighbors within one mile from the voter, and by Census Block and Census Block Group. The results are also consistent when dropping non-partisan neighbors from the denominator – calculating exposure to Democrats or Republicans out of total partisan neighbors.

I also calculate the partisan composition of each voter's household, counting the number of Democrats, Republicans, and total number of registrants who live with a given voter. 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.

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.

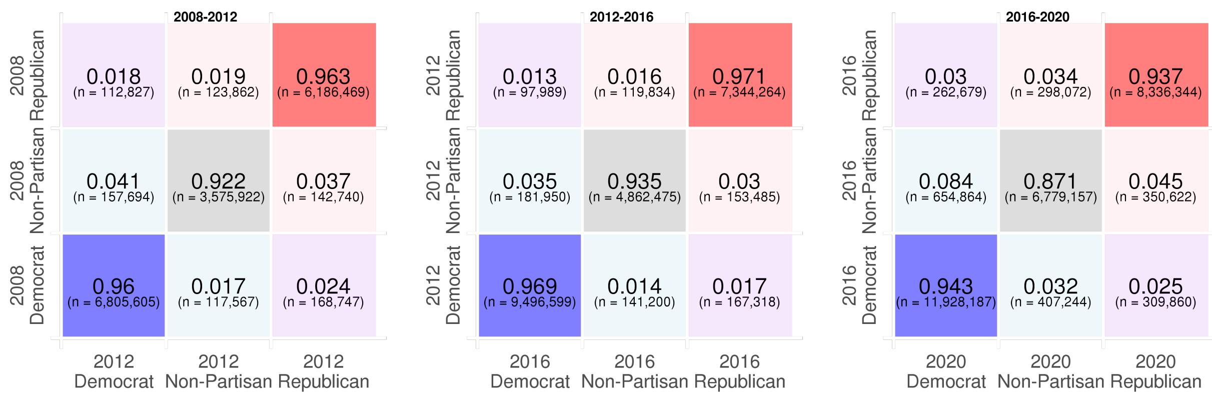


Figure 2: Partisan Transition Matrices

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.

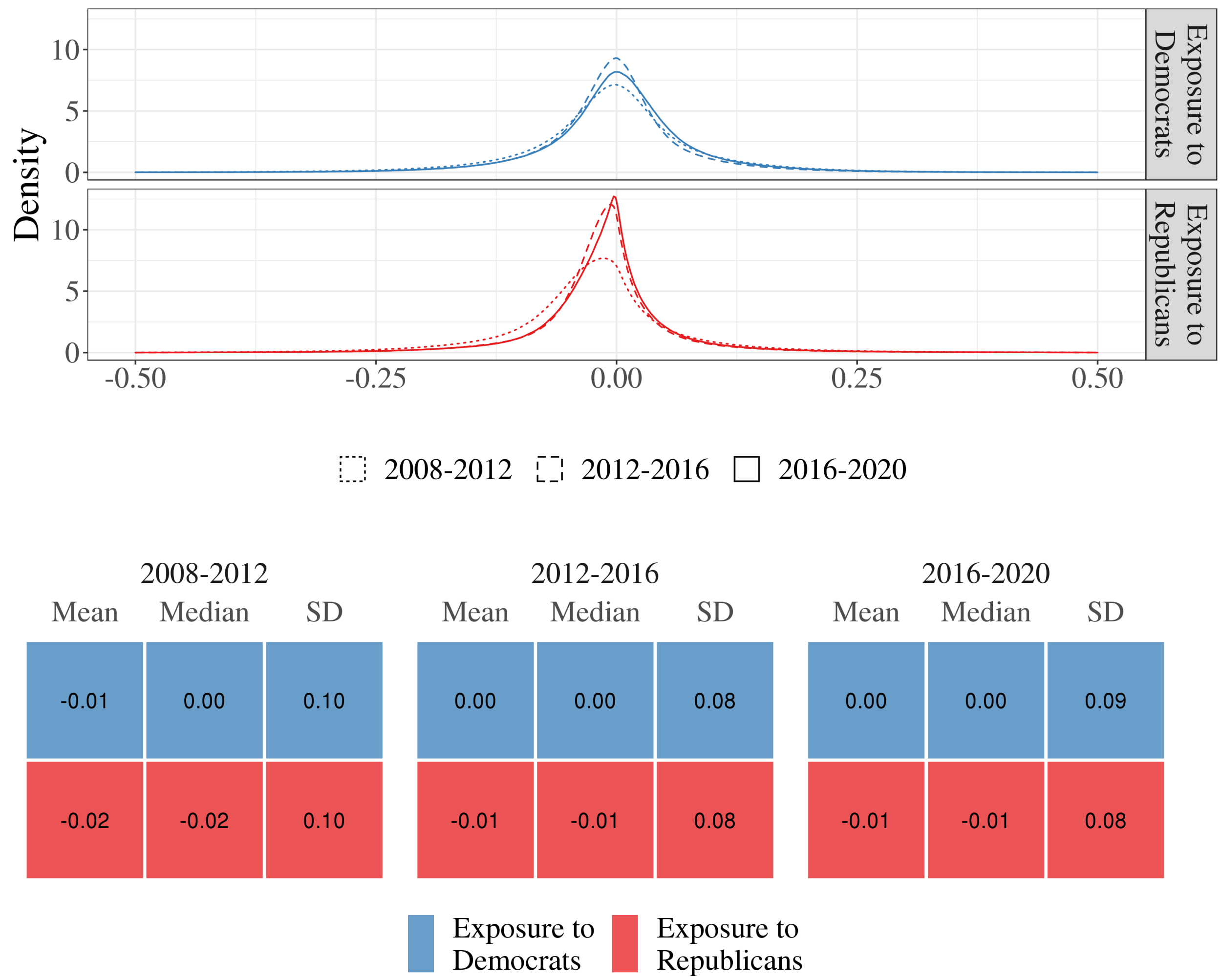


Figure 3: Distribution of Changes in Democratic and Republican Exposure

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

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

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

To better isolate the effect of exposure on registration, I create strata defined by the full interaction of voter race, gender, marital status, age decile, Zip Code, 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.

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

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 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* a 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. I also account for individual changes in marital status during the time period by controlling for the difference in binary variables for married in the first and second election years.[9]

Let $D_{i,t}$ denote a binary variable that takes 1 if voter i is a registered Democrat in election

[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] 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.

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 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[10]:

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

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.

Identifying Assumptions

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

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

and accounting for other time-variant features of neighborhoods.

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

I take several steps to address this concern. First, as discussed previously, I match on individual and contextual variables to narrow the scope of my comparison to compare most similar individuals. 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.[11] 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)).

Incorporating household partisan composition into the matching strategy and controlling for household-level changes strengthens the causal 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. Any household-level shocks

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

to partisanship are accounted for in the estimation and will not bias the neighbor exposure coefficients. For localized shocks to threaten inference, they would have to be influencing voters and their neighbors, but not their household members, as well as being independent from the other matching criteria and contextual controls. For example, the effect of local economic events on partisanship are likely accounted for by this estimation, since most external economic impacts (even those that are operating within-Zip Code and independently of race, age, gender, and starting partisan exposure) are experienced equally by household members (Mazzocco, Ruiz, and Yamaguchi, 2014).

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

To examine the sensitivity of the current effects to within-Zip Code confounding, I conduct a simulations measuring how much within-Zip Code party switching would have to occur for the estimation strategy to return estimates of the same size as the effects. The simulations demonstrate that estimation is sensitive to within-Zip Code shocks, but for such shocks to fully explain the effects they would have to occur at a magnitude not supported by the data. Simulation details are provided in Supporting Information Section S5.

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, 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 0.3-2.5 percentage point increase in the likelihood of registering with that party, depending on model, year and subset. Across the linked samples, 5.7% of voters change their party registration between presidential election cycles, so these effects constitute a 5%-40% increase over the baseline probability of changing party.

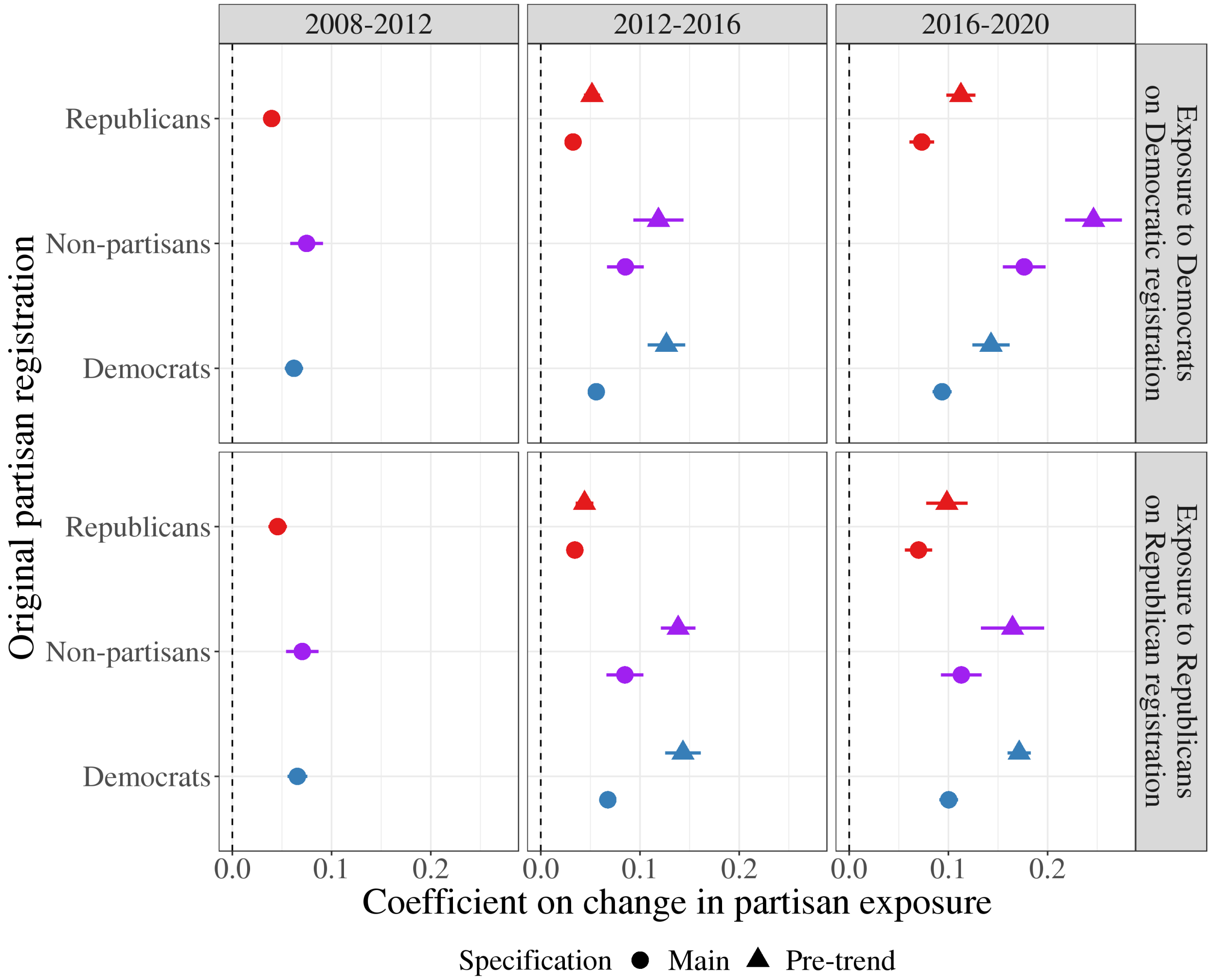


Figure 4: Effect of Partisan Exposure on Partisan Registration

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.

Figure 5 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.

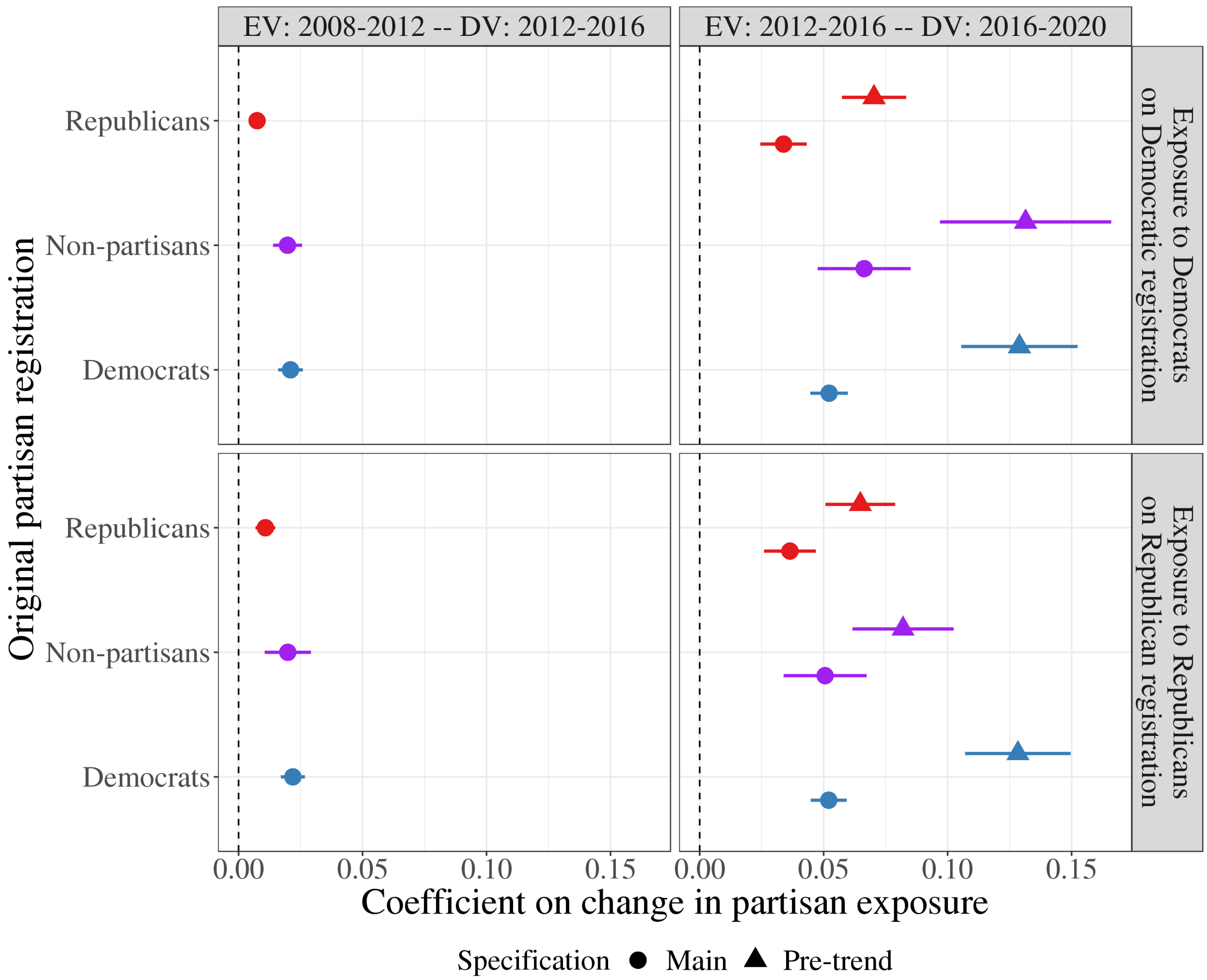


Figure 5: Effect of Partisan Exposure on Downstream Partisan Registration

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 represent the effect of changing exposure during the treatment period on changes in partisan registration during the following 4-year period. Results are plotted separately for subsets based on partisanship in the first year of the linked sample. Circular points plot coefficients from main specification and triangular points plot coefficients from pre-trend specifications. Bars plot 95% confidence intervals.

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

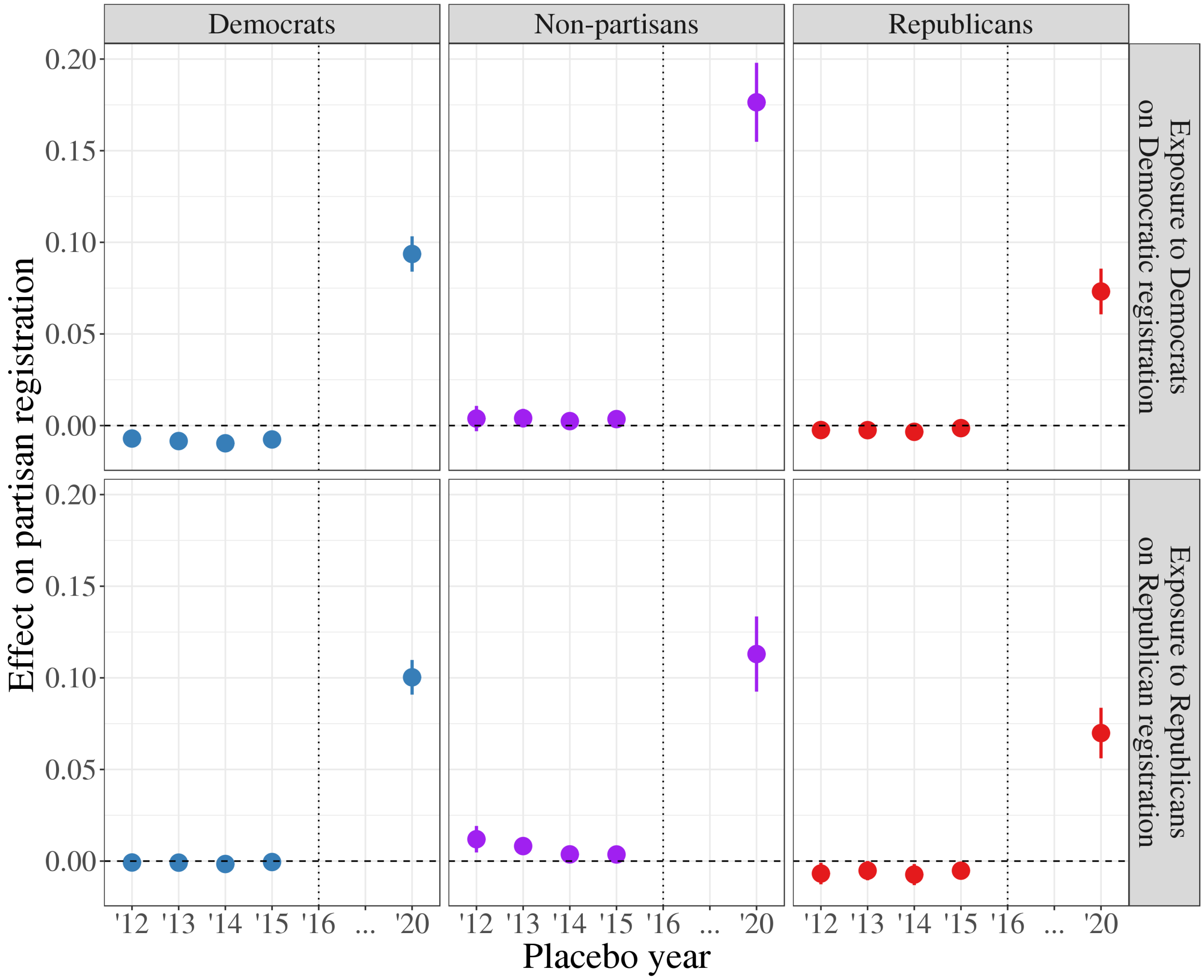


Figure 6: Placebo Trends

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

Survey Evidence of Social Influence

The panel data demonstrate that shifts in local partisan composition influence voters to change registration to match local partisanship. But these data cannot measure 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 Republican party, with response options following a 7 point ordinal scale from "None/not at all" to "A great deal". These two questions measure how voters perceive and experience their local geography, with the expectation that if voters respond to partisan exposure by changing their party, then they should say they live around more Democrats/Republicans and report greater contact with partisan neighbors when they have more neighbors from that party.

Table 1: Survey Outcomes

Survey Outcome	Scale
More Democrat or Republican neighbors	All Rep. – All Dem. (1 - 7)
Contact with Democrat neighbors	None – A great deal (1 - 7)
Contact with Repuplican neighbors	None – A great deal (1 - 7)
Neighbors know voter's party	Very uncomfortable – Very comfortable (1 - 5)

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

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

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[13] for perceptions of neighbors' partisanship, interaction with partisan neighbors, and comfort sharing partisanship with neighbors. The coefficient on Democratic exposure in Model 1 is positive, meaning that Democratic exposure predicts reporting that one's neighborhood is more Democratic than Republican. The reverse relationship is seen for the coefficient on Republican exposure in

[12] Details on the construction of the weights, and the results without weights, are provided in the Supporting Information (Section S8).

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

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.

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

The 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, and their comfort expressing their own partisanship. As such, the results illustrate the causal 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

[14]Models 5-6

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

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 increase in exposure. Cluster-robust standard errors, clustered at the county level are show in parentheses.

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. These analyses are presented in the Supporting Information S7. Additional analyses find limited support for alternative explanations, such as campaign mobilization. For example, in the Supporting Information (Section S6.1), I estimate results separately by U.S. House district to see if the results are larger in competitive districts, where campaign mobilization efforts are more concentrated – but find results are similar across districts.

The size of the data allow for not just identification of statistically significant evidence of the conversion hypothesis, but interrogation of the substantive importance of effect sizes. Considering general levels of partisan change, are the effects evidence of a meaningful influence on voter psychology, and how do they compare to other influences on party switching? Partisanship is understood to be a stable marker of political identity, and thus small changes in partisanship represent relatively large shifts (Campbell et al., 1960; Green, Palmquist, and Schickler, 2004). In the data, voters change party infrequently, with approximately 5.7% of voters changing party between presidential elections. The effect of a one standard deviation increase in partisan exposure makes voters 0.3-2.5 percentage points more likely to adopt the party of their neighbors, a 5%-40% increase over the baseline probability of changing party.

This represents a large relative increase in party switching, 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.

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