SOURCES AND EXTENT OF RISING PARTISAN SEGREGATION IN THE U.S. – EVIDENCE FROM 143 MILLION VOTERS*

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Using two datasets tracking the location and party affiliation of every U.S. voter between 2008 and 2020 in states recording partisan registration, we find that geographic segregation between Democrats and Republicans has increased year over year at all geographic levels, from Congressional Districts to Census Blocks. Areas trending Democratic have a starkly different demographic profile than those trending Republican, so the confluence of demographics, partisanship, and geography is growing. We decompose the increase in geographic partisan segregation into different sources and show that it has not been driven primarily by residential mobility but rather by generational turnover, as new voters entering the electorate cause some places to become more homogeneously Democratic, and by party switching, as existing voters leaving the Democratic party cause other places to become more Republican. The groups that most contribute to the rise in partisan segregation are young people, women, and non-white voters in Democratic-trending areas; and white and older voters in Republican-trending areas.

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I. INTRODUCTION

Concerns about rising affective and issue polarization in the U.S. and around the world (Abramowitz and Saunders 2008; Levendusky 2009; Iyengar and Westwood 2015; Boxell, Gentzkow, and Shapiro 2017; Mason 2018; Draca and Schwarz 2024; Boxell, Gentzkow, and Shapiro 2024) coincide with renewed interest in the geography of partisanship. Drawing on the literature showing that segregation along ethnic or racial lines is associated with animosity, violence, and poor governance (Massey and Denton 1993; Esteban and Ray 1994; Alesina, Baqir, and Easterly 1999; Trounstine 2016; Enos 2017), scholars and journalists alike have warned that geographic sorting of voters by party affiliation may not just fuel polarization,[1] but may eventually threaten the competitiveness and representativeness of elections, the provision of public goods, and the sustainability of democracy (Bishop 2009; Chen and Rodden 2013; Cramer 2016; Nall 2018; Levitsky and Ziblatt 2018). However, because existing work on geographic partisan segregation has largely relied on aggregate data (Sussell 2013; Rodden 2019; Kaplan, Spenkuch, and Sullivan 2022), we do not have clarity on the extent to which partisan segregation affects the makeup of an individual's immediate neighborhood, on the forces driving partisan segregation, and on the demographics of voters contributing to it.

In this paper, we study the sources and extent of rising geographic partisan segregation by leveraging individual-level administrative data from two nationwide panels including every U.S. voter in states that record party registration. Our data, provided by the commercial firms Catalist and TargetSmart, enable us to track the partisan affiliation and exact location of more than 143 million registered individuals from 2008 to 2020, for a total of over 714 million data points. We measure changes in partisan segregation at different geographic levels, map them, and decompose them into contributing factors and demographic groups.

The sorting of Democrats and Republicans at broad geographic levels, such as states and Congressional Districts, has been extensively documented (Glaeser and Ward 2006; Hopkins 2017). Within states, counties and neighborhoods may overwhelmingly support one party or another, reproducing higher-level segregation. Alternatively, state-level segregation could mask diversity at

[1] Geographic sorting may reduce the frequency of in-person interactions with out-partisans, which have been shown to mitigate both affective and issue polarization (Blattner and Koenen 2023; Fang, Heuser, and Stötzer 2025). In addition, as parties come to represent increasingly distinct geographic areas, polarization among political elites may be reinforced (Rodden 2019).

lower levels of aggregation if even in states where one party clearly dominates, voters supporting different parties live in the same areas. Although the latter situation has electoral consequences, it does not carry the same concerns about the potentially destabilizing effects of local segregation. Using electoral results, Kaplan, Spenkuch, and Sullivan (2022) document a sharp rise in geographic sorting down to the precinct level over the last five decades. Brown and Enos (2021) take geographical granularity a step further by using a 2018 snapshot of individual-level registration data similar to ours, and they find strong levels of partisan segregation even within small neighborhoods. Building on this body of evidence, our first set of results exploit the panel structure of our data to show that geographic partisan segregation increased steadily from 2008 to 2020 – between every pair of consecutive elections and across all geographic levels, from Congressional Districts and counties down to Census Tracts, Census Block Groups, and Census Blocks counting just a few dozens of residents. The weighted standard deviations of the county-level and Census Tract-level distributions of the two-party Democratic registration share (i.e., the proportion of Democrats among registered Democrats and Republicans, henceforth "Democratic share") increased by 7.7% and 4.5% during the sample period, and the fractions of Americans residing in highly segregated counties and Census Tracts (as defined based on the 10th and 90th percentiles of the baseline distributions of the Democratic share) rose by 28.3% and 15.7%, respectively.

The increasing partisan segregation *across* geographic areas is complemented by increased sorting *within* areas. We assess how unevenly Democrats and Republicans are distributed across Census Tracts within a county by computing the two-party index of Dissimilarity. That index increased by 9.6% between 2008 and 2018. Furthermore, geographic sorting increased within most counties, whether located in blue or red states. Despite differences in data processing between our two data vendors, we find very similar increases in partisan segregation across the two datasets, demonstrating the robustness of the findings.

The rise in partisan segregation across areas, as measured using the Democratic share, is clustered spatially, with a growing share of Democrats on the coasts and a growing share of Republicans in Western and Midwestern states. Counties in which the share of Democrats increases have starkly different characteristics – including a younger median age, more minority voters, and higher and faster increasing income and education – than those with a rising share of Republicans, revealing an increasing confluence of demographics and partisanship. Rather than transcending racial and educational cleavages, growing partisan differences across areas compound them.

We turn next to decomposing the increase in geographic partisan segregation into different factors. Because the decomposition requires tracking changes in individual voters' location, registration status, and party affiliation over time, this exercise has been out of reach for previous studies relying on aggregate or cross-sectional data.

We first identify possible contributing factors. Similarly to changes in racial segregation, changes in the partisan composition of an area may result from residential mobility and generational turnover (Schelling 1971; Massey and Denton 1993; Bayer, Ferreira, and McMillan 2007; Bayer et al. 2016); additionally, partisanship changes may also result from party switching. Voters expressing a preference for co-partisan neighbors and changing residence accordingly have received widespread attention from academics (McDonald 2011; Lang and Pearson-Merkowitz 2015; Gimpel and Hui 2015; Mummolo and Nall 2017; McCartney, Orellana-Li, and Zhang 2024), the media (Kaysen and Singer 2024; Ellwood 2024), and even prominent politicians.[2] Movers can increase partisan segregation even if they do not consciously choose to live with copartisans, as long as they sort on characteristics that are correlated with partisanship such as race, education, income, or climate change beliefs (Martin and Webster 2020; Bernstein et al. 2022; Ihlanfeldt and Yang 2024). Partisan segregation may also increase if voters coming of age and other new registrants disproportionately embrace the dominant party affiliation. Chyn and Haggag (2023) and Brown et al. (2023) find consistent evidence that the place in which children grow up shapes their future political behavior. Finally, adults' partisanship is also influenced by where they live currently (Huckfeldt and Sprague 1987; Johnston 2006; Cantoni and Pons 2022; Brown 2025). Those who change their party affiliation to align with the local majority further contribute to the rise in partisan segregation.[3] Understanding the respective contributions of these factors is important as they have different implications for the health of democracy: while residential sorting can be seen as a symptom of social fragmentation and political polarization, generational turnover and party-switching that benefit the dominant party may not have the same implications.

[2]For instance, former President Bill Clinton urged audiences to read "The Big Sort" from Bishop (2009) after its publication (see "Pres. Clinton Recommends The Big Sort," The Daily Yonder, 7 July 2008).

[3]While partisan preferences are generally highly persistent (Campbell et al. 1960; Green, Palmquist, and Schickler 2004), large-scale party realignments in U.S. history, such as white Southern Democrats who changed their party registration to Republican in the second half of the 20th century (Abramowitz and Knotts 2006), underscore the plausibility of widespread geographically-based party switching.

We show that the change in the Democratic share over time in a specific area can be formally written as the sum of five terms capturing residential mobility in and out of the area; generational turnover, as young voters replace voters who die; the entry and exit of adult voters, as new registrants replace those who become unregistered; party affiliation switches between Democrats and Republicans; and switches between independents and either major party. We compute the net changes in counts of Democrats and Republicans due to each factor and aggregate them across all areas trending either Democratic or Republican.

In Democratic-trending counties, generational turnover accounts for 46.9% of the change in the Democratic share, making it the main source of increasing partisan segregation. Party switching is the main factor in Republican-trending counties, with switches between Democrats and Republicans and switches involving independents accounting for 39.6% and 9.0% of the change in the Democratic share, respectively. In contrast, residential mobility only explains 12.0% and 14.1% of the change in these two groups of counties. We further show that differences in factors' relative importance in Democratic- and Republican-trending counties reflect differences in partisan tilt more than scale. For instance, the reason why generational turnover plays a more important role in Democratic-leaning counties is not that these counties have a larger share of young voters but that their young voters are more likely to register with the dominant party: In these counties, new voters are 11.9 percentage points more likely to be Democrats than the baseline fraction of Democrats, whereas in Republican-trending counties new voters are only 2.8 percentage points more likely to be Republicans than the baseline fraction of Republicans. Similarly, switches between Democrats and Republicans play a more important role in Republican-leaning areas because party switching benefits the dominant party (the Republican party) more in these places.

We finally extend our decomposition analysis to measure the contribution of different demographic groups. We show, first, that geographic partisan segregation increases for both males and females and for all age groups, but at a faster rate among younger voters. Partisan segregation also rises among white voters but decreases among Blacks, Hispanics, and voters of other races. Second, in Democratic-trending areas, the increase in the Democratic share and the contribution of generational turnover to that trend are primarily driven by youths, women, and non-white voters. In Republican trending areas, the drop in the Democratic share and the contribution of party switching to it are primarily driven by white and older voters instead.

The remainder of the paper is organized as follows. Section 2 describes the data we use in our analysis. Section 3 provides formal definitions of our two metrics of partisan segregation and presents overall trends for both. Section 4 describes our findings on the areas driving the rise in partisan segregation. Section 5 estimates the contribution of different factors to that trend. Section 6 extends the decomposition to unpack the contributions of different demographic groups. Section 7 concludes.

II. DATA

II.A. Catalist and TargetSmart data

We measure changes in partisan segregation using nationwide individual-level panel data on partisanship and exact residential location.

Our data originate in official voter lists on which U.S. citizens must register to vote in federal elections. These lists are regularly updated to reflect changes in voters' addresses and entry or exit from the electorate. Because this information is collected and maintained by states or, in some cases, counties within states, there is no publicly controlled nationwide database of registered voters, and the same voter can appear in more than one state or even more than once in the same state. In addition, some entries may remain on voter files after the voters have died. Commercial vendors obtain these lists, consolidate the data across states, account for movement and death, and sell comprehensive files containing longitudinal information on voters' location and voting behavior as well as their age, race, and gender to political campaigns and other interested parties (Hersh 2015).

Commercial vendors must make probabilistic guesses about the identity of many voters, generating discrepancies between different commercial files, with even the raw counts of registered voters differing by millions of entries (Igielnik, Keeter, and Spahn 2018). We rely on data from two distinct vendors to ensure the robustness of our findings and to allow for a longer analytical timespan: Catalist (covering even years from 2008 to 2018) and TargetSmart (covering even years from 2012 to 2020). Where possible, we replicate our analyses using both datasets. Furthermore, due to differences in data availability, the two datasets are better suited for analysis at different levels. The TargetSmart data include the full names and exact addresses of individuals and can thus be used at any level of geography. In contrast, our version of the Catalist data does not include individual addresses or any other identifying information, and it requires aggregation to larger geographic levels. The Catalist data also span a congressional redistricting cycle in 2010, where the districts for Congress and other electoral districts were redrawn, and Catalist adopted 2010 Census Tract FIPS codes starting in 2016, preventing us from tracking changes at the Census Tract level across that year with these data.[4] Therefore, we primarily use the Catalist data to examine county-level segregation and TargetSmart for other geographic levels. To our knowledge, we are the first large-scale study to use commercial files from two different vendors.

II.B. Measuring Partisanship

Registered party membership, which prior research has shown to reflect both voters' self-declared partisan identity and their ideological leanings (Bartels 2000; Gerber, Huber, and Washington 2010), is available in 29 states, along with the District of Columbia, where voters can declare membership in a political party when registering to vote (Democrat, Republican, or one of many minor parties).[5] We focus our analysis on these states and determine voters' partisanship based on this official registration. Party registration is not mandatory, and the percentage of registered voters not affiliated with the Democratic or Republican parties rose from 25.9% to 30.6% between 2008 and 2018, in party affiliation states.

We test the robustness of our results by using aggregate vote shares as a proxy for partisan ideology and including all states in the sample. An important caveat, which also applies to previous studies using such data, is that changes in party vote shares between elections may reflect election-specific factors rather than shifts in underlying partisan preferences.

II.C. Data Cleaning

Appendix A outlines the steps we used to clean the Catalist and TargetSmart data. In particular, Catalist is more aggressive in de-duplicating records across different states than TargetSmart, so that each individual is uniquely identified by a time-invariant ID and by year in the Catalist data. In the TargetSmart data, we use voters' names and addresses to build on the work done by TargetSmart

[4]FIPS codes are codes from the Federal Information Processing Standard that uniquely identify counties and other geographic units.

[5]Idaho started recording partisan registration in 2013 and is thus not included in our analyses, which span from 2008 to 2020.

and further de-duplicate voter records within and across states. After completing this processing, restricting the sample to party-affiliation states, and removing flagged observations, the number of registered voters is lower in the TargetSmart data than in the Catalist data, in years covered by both datasets, as shown in Appendix Table A.1. In total, we use 610,588,611 voter × year observations from the Catalist data, corresponding to 142,686,630 registered voters, and 465,331,530 voter × year observations from the TargetSmart data, corresponding to 132,001,456 registered voters.

Year-by-year statistics on the overall shares of Democrats, Republicans, Blacks, Hispanics, whites, and males reported in Appendix Table A.1 are very similar across the two datasets, with a slightly larger proportion of whites in the TargetSmart data.

III. CHANGES IN GEOGRAPHIC PARTISAN SEGREGATION

III.A. Two Metrics of Geographic Partisan Segregation

We first document overall trends in geographic partisan segregation. We consider multiple geographic levels to assess the sensitivity of our results to the choice of areal unit. Because we use individual data, we could aggregate them to any arbitrary scale, but we choose to examine geographic units that are politically and socially meaningful and are commonly used in social science. In the main analysis, we focus on counties and Census Tracts. Census Tracts generally include between 1,200 and 8,000 people, and contain an average of 2,527 voters in our data. We use Census Tracts to represent neighborhoods, following the literature (Sharkey and Faber 2014; Ansolabehere et al. 2025). In the Appendix, we provide results using Congressional Districts, as well as Census Block Groups and Census Blocks, which are smaller units than Census Tracts.

We employ two metrics of partisan segregation: the two-party Democratic registration share and the two-party index of Dissimilarity.

The two-party Democratic registration share, which we refer to as the *Democratic share* for conciseness, measures geographic sorting *across* units.[6] Our main metric of interest, it is computed as the share of Democrats and Republicans that are Democrats in a given geographic unit:

$$\text{Democratic share}_{i,t} = \frac{\sum_{v \in i,t} D_{v,t}}{\sum_{v \in i,t} (D_{v,t} + R_{v,t})},$$

[6] Some papers call this metric "Exposure" (Massey and Denton 1993; Brown and Enos 2021).

where $D_{v,t}$ and $R_{v,t}$ are dummies equal to 1 if voter v is registered as Democrat and Republican, respectively, in year t in unit i, and 0 otherwise. This measure ranges from 0 (when there is no Democrat) to 1 (when there is no Republican).[7] Values of the Democratic share that are closer to 0 or 1 indicate higher partisan homogeneity.

The two-party *index of Dissimilarity*, our second metric, measures geographic sorting *within* units by assessing how unevenly members of the two parties are distributed across subunits within a geographic unit (Jakubs 1977; Massey and Denton 1988). It is defined as:

$$\text{Index of Dissimilarity}_{i,t} = \frac{1}{2}\sum_{j\in i}\left|\frac{\sum_{v\in j,t} D_{v,t}}{\sum_{v\in i,t} D_{v,t}} - \frac{\sum_{v\in j,t} R_{v,t}}{\sum_{v\in i,t} R_{v,t}}\right|,$$

where j is a generic subunit within i.[8] This index ranges from 0 (complete evenness) to 1 (complete segregation). It corresponds to the sum of the proportion of Democrats and the proportion of Republicans who would have to move to make Democrats and Republicans evenly spread throughout unit i.

III.B. Changes in the Democratic Share

Figure I displays the distribution of the Democratic share for 2008 and 2018 at the county level and for 2012 and 2020 at the Census Tract level. Each geographic unit is weighted by its count of registered voters. Red shading indicates a greater Republican share, while blue shading represents a larger Democratic share. The dotted and solid lines correspond to the earlier and later periods, respectively. The widening of these distributions indicates that partisan segregation has grown across both counties and Census Tracts: more voters live in areas that are homogeneously Democratic or Republican at the end of the period than at the beginning, resulting in lower exposure to the other party in their residential environment. Overall, the standard deviation of the Democratic share rose from 0.155 to 0.167 at the county level and from 0.200 to 0.209 at the Census Tract level,

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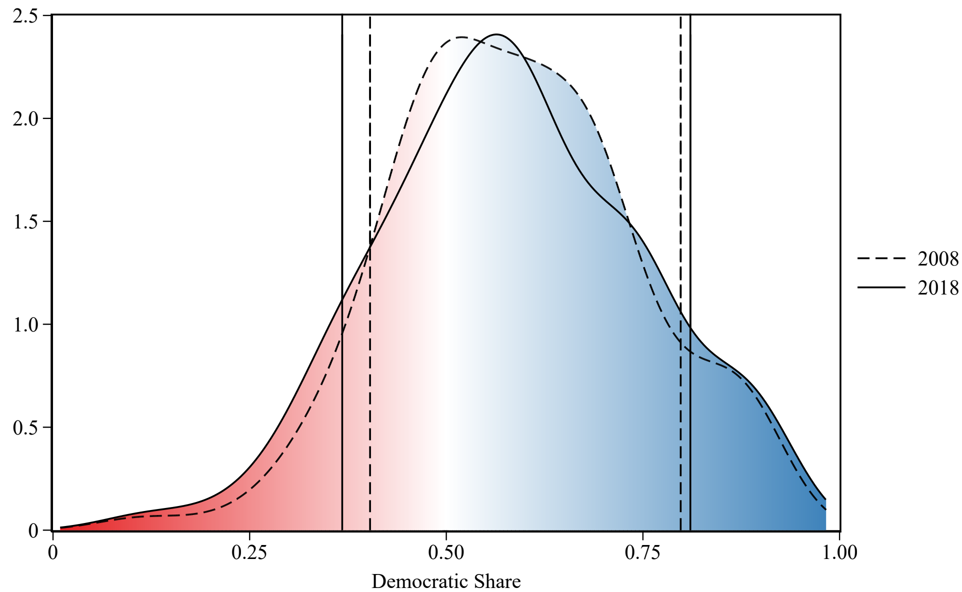
[7]The Democratic share excludes non-partisans from the denominator. In contrast, Appendix Tables B.1 and B.2 report the yearly mean and standard deviation of the shares of Democratic and Republican registrants, using the total number of registrants as denominator. We first observe that both shares decrease over time, due to the growing share of independents. Second, while the standard deviation of the share of Democrats fluctuates, the standard deviation of the share of Republicans increases consistently, indicating that counties and Census Tracts become increasingly likely to contain either a small or a large proportion of Republicans, consistent with Figure I.

[8]Our main calculations use Census Tracts as subunits, following the literature (Bureau 2021; Hwang and McDaniel 2022).

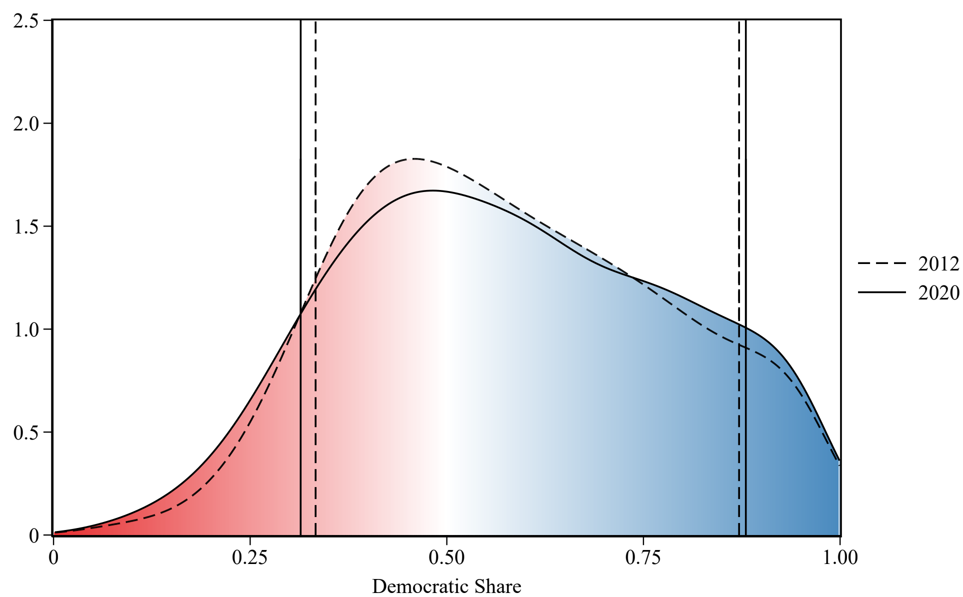
representing increases of 7.7% and 4.5%, respectively (Appendix Table B.3).

FIGURE I
Distribution of the Democratic Share

(a) County-Level Distribution, 2008 and 2018



(b) Census Tract-Level Distribution, 2012 and 2020



Notes: We show kernel density plots of the Democratic share. All kernel density estimates are weighted by counts of registered voters in a given geographic unit-year and use a Gaussian kernel with bandwidth of 0.05. In each plot, vertical lines represent the 10th (vertical lines on the left tail of each plot) and 90th percentiles (vertical lines on the right tail of each plot). Panel A uses the county-level Catalist data for the 2008 and 2018 elections. Panel B uses the Census Tract-level TargetSmart data for the 2012 and 2020 elections.

These changes mark a substantial shift in the proportion of voters residing in highly segregated areas over a relatively short period. In 2008, 20% of U.S. registered voters lived in counties where the Democratic share was below 0.403 or above 0.798 (the 10th and 90th percentiles of the distribution). By 2018, this figure had risen to 25.7%, indicating a 28.3% increase in Americans living in highly segregated counties over 10 years. This shift translates to an additional 6.1 million voters in 2018 residing in such counties. Similarly, at the Census Tract level, the share of registered voters living in extremely segregated areas grew by 15.7% between 2012 and 2020, with 23.1% of voters in 2020 living in Census Tracts above the 2012 90th percentile (0.872) or below the 2012 10th percentile (0.333), translating to 3.2 million more voters living in extremely segregated Census Tracts in 2020 than in 2012.

Beyond comparing the distribution of the Democratic share at the beginning and at the end of the period, we also plot them for every election year, using both the Catalist and TargetSmart data. As shown in Appendix Figure B.1, geographic partisan segregation across counties and Census Tracts has consistently increased between each pair of consecutive elections (also see Appendix Table B.3).

In Appendix Figure B.2 and Table B.4, we present year-by-year distributions of the Democratic share at geographic levels that are either larger or smaller than counties and Census Tracts: Congressional Districts, Census Block Groups, and Census Blocks. We use the TargetSmart data for these analyses because these data feature detailed residential address information and consistent Congressional District boundaries between 2012 and 2020 (i.e., the coverage of the TargetSmart data does not span a Decennial Census, which would result in redistricting). Trends and distributions at the Congressional District level largely reflect those observed at the county and Census Tract levels. Compared to larger geographic units, Census Block Groups and Census Blocks exhibit higher baseline levels of concentration of registrants in homogeneously Democratic or Republican areas, as evidenced by the larger standard deviations. Nonetheless, the distribution also widens over time at these smaller geographic levels.

To test the statistical significance of these changes, we first define the contribution of any geographic unit to the variance of the Democratic share at time t.[9] Let $x_{i,t}$ be the Democratic share

[9]Note that we consider units' contribution to the variance of the Democratic share because this measure is additive, unlike units' contribution to the standard deviation. In contrast, Appendix Tables B.3 and B.4 consider the standard deviation of the Democratic share since, unlike the variance, the standard deviation is expressed on the same scale as the mean.

in unit i at time t, and $w_{i,t}$ the unit's weight defined as the fraction of registered voters living in that unit, so that $\sum_{i=1}^{n} w_{i,t} = 1$. The weighted variance σ_t^2 of the Democratic share at time t is given by:

$$\sigma_t^2 = \frac{\sum_{i=1}^{n} w_{i,t} \times (x_{i,t} - \mu_t)^2}{\sum_{i=1}^{n} w_{i,t}},$$

where the weighted mean μ_t is:

$$\mu_t = \frac{\sum_{i=1}^{n} w_{i,t} \times x_{i,t}}{\sum_{i=1}^{n} w_{i,t}}.$$

We define the contribution of unit i to the weighted variance as:

$$c_{i,t} = w_{i,t} \times (x_{i,t} - \mu_t)^2.$$

We then estimate the following model:

$$c_{i,t} = \alpha + \beta t + \gamma_i + \epsilon_{i,t}, \tag{1}$$

where t represents time measured as the order of the election (one for the first election, two for the second one, etc.) and the γ_i's denote a full set of unit fixed effects. We use two observations per unit, corresponding to the first and last elections in the sample. The coefficient β measures the extent to which the average unit's contribution to the weighted variance changed over time. Standard errors are clustered at the unit level.

Table I, Panel A presents the results for each geographic level based on the Catalist and TargetSmart data. All coefficients are positive, indicating that the average unit is further from the mean Democratic share at the end of the period than at the beginning, consistent with the widening distribution of the Democratic share observed in Figure I. Furthermore, the increase in geographic partisan segregation over time is statistically significant at all geographic levels.

III.C. Changes in the Index of Dissimilarity

In addition to the sorting of partisans *across* geographic areas in the United States, we also find that segregation is increasing *within* geographic areas. As shown in Figure II, the weighted distribution

TABLE I
RISE IN ACROSS AND WITHIN-UNITS PARTISAN SEGREGATION

	County		Census Tract	Congr. Dist.	Census Block Group	Census Block
	Catalist	TargetSmart	TargetSmart	TargetSmart	TargetSmart	TargetSmart
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Outcome: Contribution to the Weighted Variance of Democratic Share					
Time	0.0020 ***	0.0017 *	0.0019 ***	0.0019 **	0.0019 ***	0.00087 ***
	(0.0007)	(0.0010)	(0.0001)	(0.0008)	(0.0001)	(0.00002)
R^2	0.937	0.931	0.924	0.940	0.920	0.833
Observations	2,746	2,758	81,871	368	243,005	5,665,403
Unit FEs	✓	✓	✓	✓	✓	✓
	Panel B. Outcome: County-Level Index of Dissimilarity					
Time	0.0039 ***	0.0013 ***	-	-	-	-
	(0.0004)	(0.0005)	-	-	-	-
R^2	0.976	0.967	-	-	-	-
Observations	2,494	2,493	-	-	-	-
Unit FEs	✓	✓	-	-	-	-

Notes: Panel A reports estimates from linear regressions of a geographic unit's contribution to partisan segregation on election years. Similarly, Panel B reports estimates from linear regressions of a county's index of Dissimilarity (using Census Tracts as subgeographies) on election years. We use two observations per unit, corresponding to 2008 and 2018 for the regressions using Catalist data, and to 2012 and 2020 for the regressions using TargetSmart data. All regressions, as well as year averages used to construct the dependent variable in Panel A, are weighted by counts of registered voters in a given geographic unit in a given year. Since almost every Congressional District in Florida, North Carolina, and Pennsylvania was affected by court-mandated intercensal redistricting, the sample in column 4 excludes all districts from these three states. Similarly, we do not report Census Tract-level regressions using Catalist data because Census Tract identifiers in the Catalist data changed after the 2010 decennial census.

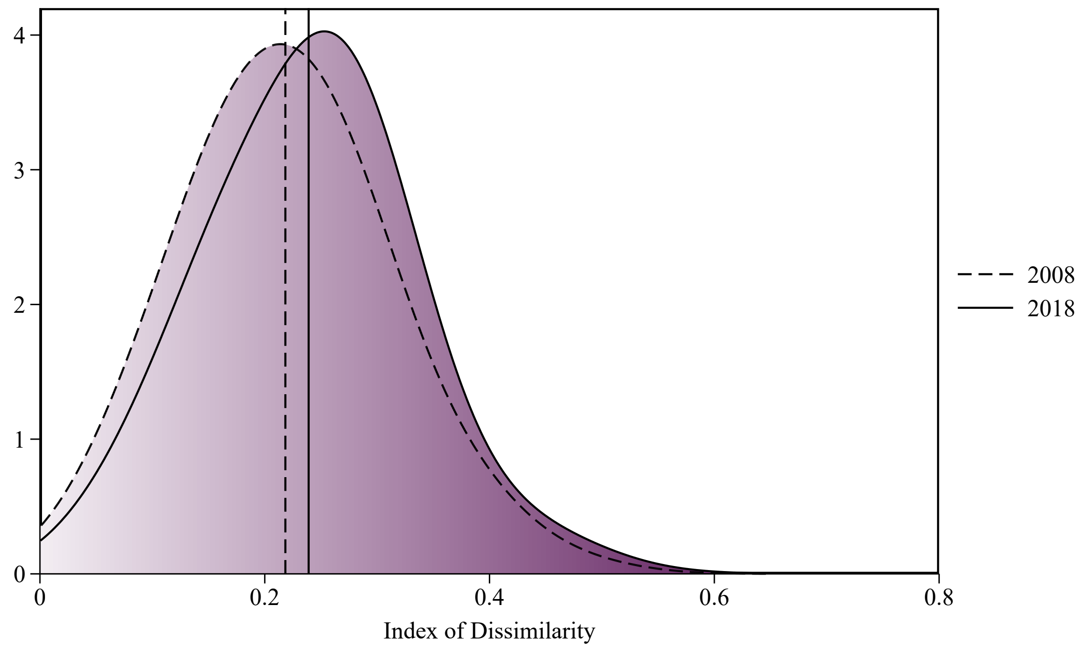
*** p < .01, ** p < .05, * p < .10

of the index of Dissimilarity at the county level shifted rightward between 2008 and 2018, indicating that voters of a given county are increasingly sorted into different Census Tracts based on partisan affiliation. On average, the county-level index of Dissimilarity increased by 2.1 points (9.6%, Appendix Table B.5).

We also observe a shift of the distribution of the index of Dissimilarity to the right at the Congressional District level (Appendix Figure B.3c). The mean index of Dissimilarity increased consistently year over year, except between 2018 and 2020 (Appendix Tables B.5 and B.6).

FIGURE II

Distribution of the County-Level Index of Dissimilarity, 2008 and 2018, Catalist Data



Notes: We show kernel density plots of the county-level index of Dissimilarity based on the 2008 and 2018 Catalist data, using Census Tracts as subunits and weighting by counts of registered voters in a given county-year. Vertical lines represent year-specific (weighted) means. All kernel density estimates use a Gaussian kernel with bandwidth of 0.05.

Finally, we estimate equation (1) using Index of Dissimilarity$_{i,t}$ as the dependent variable. As shown in Table I, Panel B, the increase in the county-level index of Dissimilarity over time is significant at the 1% level whether we use the Catalist or TargetSmart data. From these results, we infer that the widening of the distribution of the Democratic share at the Census Tract level shown in Figure I is not just the by-product of sorting at higher geographic levels. Instead, geographic partisan segregation also increases across Census Tracts of the same county.

III.D. Robustness Checks Using Alternative Data Sources

We now use aggregate data from Dave Leip's Atlas of U.S. Presidential Elections (Leip 2021) to check that the rise in geographic partisan segregation is not limited to states recording party affiliation. The finest geographic level at which Dave Leip's data are available for all years in our main analyses is the county. Appendix Figure B.4 first shows the distribution of the two-party Democratic vote share at that level for all presidential elections from 2008 to 2020. Once again, we observe an overall widening of the distribution over time. The standard deviation of the distribution increased by 18.1% between 2008 and 2020 (Appendix Table B.7). It rose between any two presidential elections until 2016 and decreased slightly between 2016 and 2020.

Second, we compute *nationwide* indices of Dissimilarity using the full country as the larger (and unique) geographic unit, and based either on registration data or vote counts. Consistent with the increase in the average county- and Congressional-District level indices of Dissimilarity observed in Figure II and Appendix Figure B.3, Appendix Figure B.5 shows an increase in the nationwide index computed using the Catalist and TargetSmart registration data between 2008 and 2020, irrespective of the choice of subunit (Congressional Districts, counties, Census Tracts, Census Block Groups, or Census Blocks).[10] Next, Appendix Figure B.6 plots the trend in the nationwide index of Dissimilarity using individual registration data from Catalist and TargetSmart as well as county-level aggregate registration data and vote counts from Dave Leip's Atlas. All series use counties as subunits. The Catalist and TargetSmart series are identical as the series using counties as subunits in Figure B.5. As expected, we observe a very similar increase in the nationwide index of Dissimilarity between 2008 and 2020 using county-level aggregate registration data, in the set of states with partisan registration. Furthermore, the index of Dissimilarity computed using presidential vote counts also increased during this period. This upward trend is similar whether we restrict the sample to partisan registration states or include all states, and it had already begun between 1988 (the first year in Dave Leip's vote count data) and 2008.

In sum, the increase in geographic partisan segregation extends beyond the period and states for which individual-level party affiliation data are available.

IV. AREAS DRIVING THE RISE IN PARTISAN SEGREGATION

IV.A. Classifying Geographic Units as Increasing versus Decreasing Segregation

While partisan segregation has increased across the United States, this trend has not been uniform in all areas. We compute the change in each unit i's contribution to the variance of the Democratic

[10] At any point in time, the nationwide index of Dissimilarity is larger when using smaller geographic subunits. This is consistent with the fact that the distribution of the Democratic share is wider for smaller subunits (Appendix Figure B.2). The increase in the nationwide index of Dissimilarity is comparable for different subunits, and the trends for a given subunit are very similar in the TargetSmart and Catalist data.

share between t and $t+1$ as:

$$\Delta c_i = c_{i,t+1} - c_{i,t}, \tag{2}$$

where $c_{i,t}$ is defined as in Section III.B. Unit i contributes to increasing geographic partisan segregation (as measured based on the Democratic share) if $\Delta c_i > 0$.

Of 1,373 counties located in states that record partisan registration, 62.1% (representing 59.9% of the registrants in 2018) contributed to the increase in segregation between 2008 and 2018, while the remaining counties went against that trend. Among the counties contributing to the increase in segregation, 10.7%, accounting for 53.7% of the registrants, experienced an increase in the Democratic share. The difference between the two latter numbers results from the fact that counties trending Democratic are much more populated than those that shifted more Republican.[11]

Turning to our second metric of geographic partisan segregation, we find that the index of Dissimilarity increased in 71.4% of counties, accounting for 81.3% of the registrants, between 2008 and 2018.

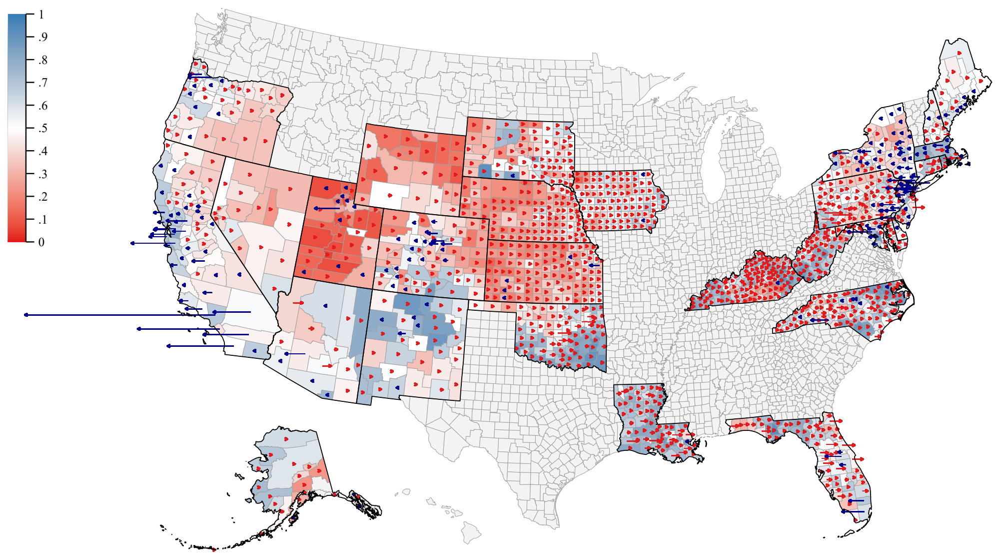
IV.B. Location of Areas Contributing to Increasing Partisan Segregation

To identify the areas contributing to the rise in geographic partisan segregation across units, Figure IIIa shows counties' initial partisan composition and its change over the subsequent decade, in states that track partisan affiliation. Counties are shaded by their Democratic shares in 2008, using the Catalist data. Darker blue represents a stronger Democratic share, and darker red a stronger Republican share. Arrows are colored blue for counties that became more Democratic between 2008 and 2018, and red for counties that became more Republican, and their size is proportional to the magnitude of the change in the Democratic share, after weighting by baseline counts of registered voters in each county. The Democratic share increased the most in large metropolitan coastal counties, especially in California, Florida, and the Northeast, which were already predominantly Democratic at baseline. Fewer instances of Democratic gains occurred in places that were initially Republican. In contrast, the Republican share grew in diverse regions, including not just Republican

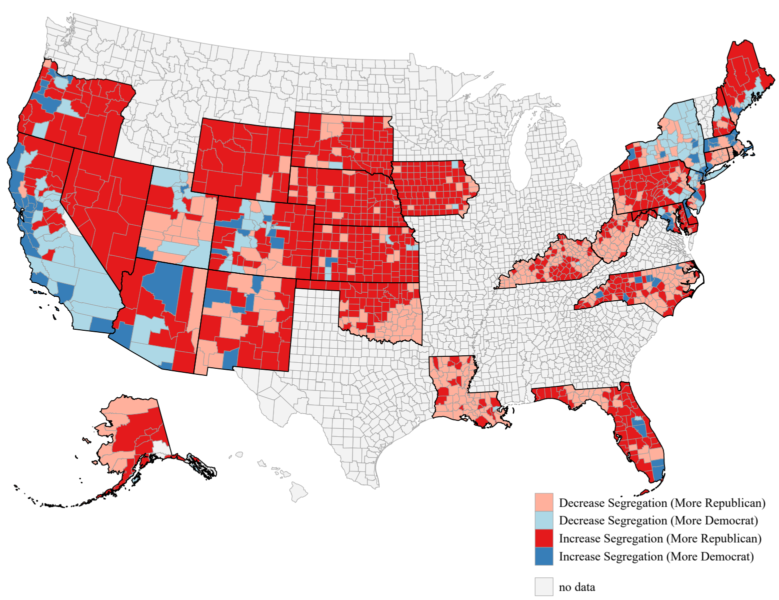
[11] Similarly, among the counties that went against the trend of increasing segregation, 22.1%, accounting for 55.0% of the registrants, became more Democratic.

FIGURE III
Change in the County-Level Democratic Share and in Partisan Segregation, 2008 to 2018, Catalist Data

(a) Change in the County-Level Democratic Share, 2008 to 2018



(b) Counties Contributing to versus Resisting the Rise in Partisan Segregation, 2008 to 2018



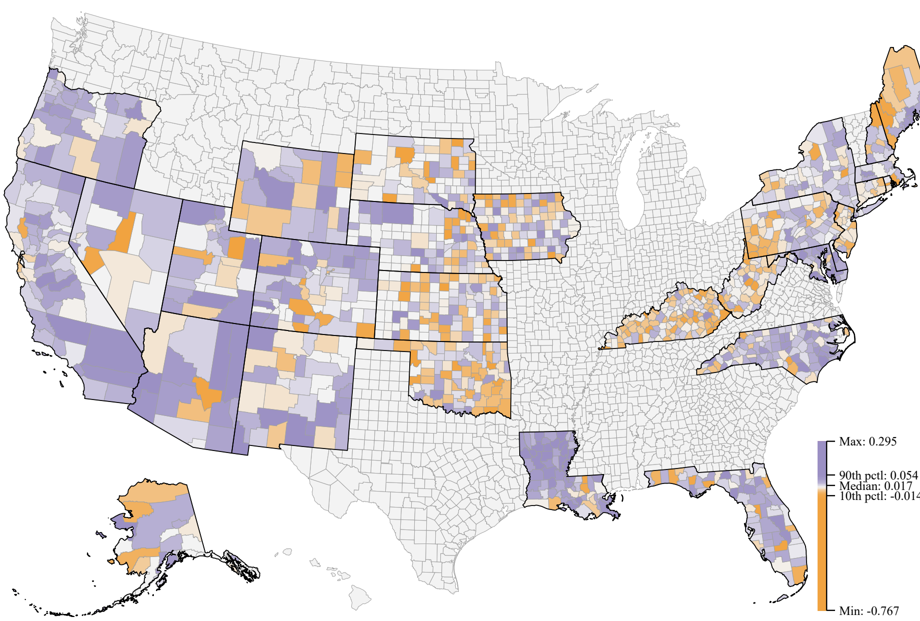
Notes: In Panel A, for the 29 U.S. states (plus D.C.) that record party affiliation, counties are shaded red (more Republican) to blue (more Democratic) based on the level of the Democratic share in 2008. Blue (resp. red) arrows mean that a county's Democratic share increased (resp. decreased) between 2008 and 2018. Arrow length is proportional to the magnitude of the change in the Democratic share, after weighting by baseline counts of registered voters in the county. Panel B shows counties that experienced an increase (colored in blue) versus a decrease (colored in red) of the Democratic share between 2008 and 2018. Light (resp. dark) shades of a color denote counties that contributed to reducing (resp. increasing) partisan segregation, by reducing (resp. increasing) the variance of the Democratic share. Both maps use 2008 and 2018 Catalist data.

areas but also some areas that had a higher Democratic base, such as counties in the Southwest, South, and the coal belt regions of Kentucky, West Virginia, and Pennsylvania.

Next, Figure IIIb shades counties by whether or not they trended Democratic or Republican and by whether or not they contributed to the increase in partisan segregation. The rise in partisan segregation is clustered spatially on the East and West coasts, for Democratic-trending places, and in Western and Midwestern states as well as Florida, Oklahoma, Maine, and Pennsylvania, for Republican-trending places.

To identify the areas experiencing an increase in segregation *within* their boundaries, Figure IV displays a county-level map of the change in the index of Dissimilarity, based again on the Catalist data.[12] We observe that most counties, whether located in blue or red states, experienced a rise in the index of Dissimilarity from 2008 to 2018. Exceptions include counties in rural areas of Midwest states such as Oklahoma, Kansas, and South Dakota, in parts of Rust Belt states such as western Pennsylvania, West Virginia, and Kentucky, and in inland parts of Maine.

FIGURE IV
Change in the County-Level Index of Dissimilarity, 2008 to 2018, Catalist Data



Notes: For counties in the 29 states plus D.C. that record party affiliation, darker shades of purple (resp. orange) denote larger increases (resp. decreases) of the county-level index of Dissimilarity between 2008 and 2018. The map is based on Catalist data, using Census Tracts as subunits.

[12] Appendix Figures C.1 and C.2 reproduce Figures III and IV using TargetSmart data, 2012-2020. The maps look very similar.

IV.C. Characteristics of Areas Contributing to Increasing Partisan Segregation

Table II uses Census and voter file data to compare the characteristics of counties classified by whether or not they contributed to increased partisan segregation across areas and whether they were trending Democratic or Republican, as in Figure IIIb.[13] On average, Democratic-trending counties (columns 1 and 3) are characterized by a younger median age, larger share of foreign-born and non-white populations, much higher population density, higher median income, higher share of college-educated individuals, and lower homeownership than Republican-trending counties (columns 2 and 4). We obtain qualitatively similar results when using the TargetSmart data for 2012-2020 at the county and Census Tract levels (Appendix Tables C.1 and C.2).

Differences between counties with an increasing versus declining Democratic share are present both for counties contributing to the rise in partisan segregation (columns 1 and 2) and for those resisting that trend (columns 3 and 4), but they are systematically much more pronounced in the former case, revealing an increasing confluence of demographics and partisanship. For instance, population density is 18 times higher (7,381 inhabitants per square mile against 416) in Democratic versus Republican-trending counties contributing to the rise in segregation, relative to a ratio of 1.6 for Democratic versus Republican-trending counties where partisan segregation is decreasing (1,668 against 1,032). Similarly, the differences in the share of non-white population and college-educated individuals between Democratic and Republican-trending counties are 30.3 and 13.2 percentage points in the first group (53.9% against 23.6% and 37.7% against 24.5%), compared to 10.8 and 4.8 percentage points in the second group (40.0% against 29.2% and 32.5% against 27.7%).

Appendix Tables C.3 and C.4 further display *changes* in demographic variables over time in counties contributing to or resisting partisan segregation. Areas trending Democratic saw larger increases in share of college-educated individuals and in median income than areas trending Republican, thus strengthening the clustering of Democratic votes in higher income and more highly-educated areas and the correlation between partisanship and socioeconomic status.[14]

[13]The table draws on 2015 5-year American Community Survey data aggregated at the county level and 2008 voter file data from Catalist. All figures are averages weighted by county-level counts of registered voters in 2008.

[14]We cannot replicate this analysis for Census Tracts because 2010 and 2020 Decennial Census data at the Census Tract level use different geographic identifiers (i.e., 2010 Census Tract FIPS codes for the 2010 data and 2020 Census Tract FIPS codes for the 2020 data).

TABLE II

CHARACTERISTICS OF COUNTIES CONTRIBUTING TO THE RISE IN PARTISAN SEGREGATION VERSUS RESISTING THAT TREND, CATALIST DATA

	Increase Segregation		Decrease Segregation	
	Democratic-Trending	Republican-Trending	Democratic-Trending	Republican-Trending
	(1)	(2)	(3)	(4)
Panel A. Census Statistics				
Total population	653,058	61,787	362,816	76,110
Median age	37.18	40.78	37.14	39.38
Share female	0.513	0.505	0.507	0.510
HHI ethnic homogeneity	0.403	0.638	0.499	0.587
Share foreign-born	0.256	0.073	0.150	0.086
Share non-white	0.539	0.236	0.400	0.292
Population/Sq. mile	7,381	416	1,668	1,032
Share urban population	0.957	0.706	0.897	0.748
Median income	63,627	51,273	63,335	53,271
Gini index	0.486	0.445	0.456	0.459
High-school degree or above	0.856	0.879	0.872	0.872
Bachelor's degree or above	0.377	0.245	0.325	0.277
Share homeowners	0.560	0.699	0.658	0.688
Panel B. Voter File Statistics on Registered Population				
Democrats	0.504	0.368	0.365	0.503
Independents	0.283	0.232	0.267	0.252
Republicans	0.213	0.400	0.368	0.246
Black	0.145	0.058	0.075	0.109
White	0.614	0.882	0.769	0.824
Hispanic	0.155	0.038	0.103	0.042
Number of counties	91	762	115	405

Notes: The table reports average demographic characteristics of counties that contributed to the increase in partisan segregation and of counties that decreased segregation, separately for counties that trended Democratic or Republican (i.e., counties that featured an increase versus a decrease in Democratic share between 2008 and 2018). All figures are weighted by county-level counts of registered voters in 2008, except for total population figures that are unweighted. Census statistics in Panel A are based on 2015 5-year American Community Survey Data aggregated at the county level. Voter file statistics in Panel B are based on the 2008 Catalist data.

V. FACTORS DRIVING THE INCREASE IN PARTISAN SEGREGATION

V.A. *Decomposing the Increase in Segregation into Contributing Factors*

The increase in geographic partisan segregation can be driven by residential mobility, generational turnover, entry and exit of adult voters, and changes in partisanship. The data enable us to disentangle these different forces because they are at the individual level and track voters who move across areas. This task would be infeasible using aggregate data.

Residential mobility (factor 1) refers to registered voters moving across areas within the U.S. *Generational turnover* (factor 2) occurs as young adults aged 25 and below register for the first time and as older voters pass away. Additionally, we account for the *entry and exit of adult voters* (factor 3). Adult entries include voters aged over 25 who get registered for the first time, without appearing in the data at baseline, and voters who re-register (i.e., voters who appear in the data as unregistered at baseline and as registered at endline), regardless of their age.[15] Adult exits capture registered voters becoming unregistered without being recorded as deceased.[16] Changes in the partisanship of residents in a given area can also contribute to segregation. These partisan affiliation changes refer to voters who were registered at baseline and endline and who switched party affiliation in between. We consider *switches between Democrats and Republicans* (factor 4) as well as *switches between independents and either major party* (factor 5). We classify individuals who move across areas while also changing parties as movers.

To assess the role played by these factors in the increase in partisan segregation, we measure their contribution to the change in the Democratic share between years y_1 and y_2. For any unit i, that change can be written as follows, after using partial derivatives:

[15] While the median age of new entrants into the electorate is 26 in the Catalist data, 33.2% of new registrants are over 34 years old. Among adult entries, we include new registrants aged over 25, representing 3.2% to 5.4% of registered voters in each electoral year in the Catalist data. These adult entrants consist of natural-born U.S. citizens becoming politically active for the first time, as well as newly naturalized citizens gaining the right to vote.

[16] As shown in Appendix Table D.1, the TargetSmart data include fewer deregistered voters but more voters who died than the Catalist data. These discrepancies likely stem from challenges in accurately tracking voter status over time and from the two vendors using different procedures to accomplish this task.

$$\Delta_i \frac{D}{(D+R)} \approx \frac{R_{i,y_1}}{(D_{i,y_1}+R_{i,y_1})^2}\Delta_i D - \frac{D_{i,y_1}}{(D_{i,y_1}+R_{i,y_1})^2}\Delta_i R$$
$$\approx \sum_f \left(\frac{R_{i,y_1}}{(D_{i,y_1}+R_{i,y_1})^2}\Delta_i D_f - \frac{D_{i,y_1}}{(D_{i,y_1}+R_{i,y_1})^2}\Delta_i R_f \right),$$

where Δ_i is an operator indicating changes between y_1 and y_2 in unit i, R_{i,y_1} and D_{i,y_1} are counts of Republicans and Democrats in the unit in y_1, and $\Delta_i D_f$ and $\Delta_i R_f$ denote net changes in counts of Democrats and Republicans due to factor f. For instance, $\Delta_i D_f$ is equal to the number of Democrats who moved in the unit minus the number of Democrats who moved out, for factor 1, and to the difference between the number of Republicans who became Democrats and the number of Democrats who became Republicans, for factor 4.[17]

We define the contribution of factor f to the change in the Democratic share in unit i as:

$$\lambda_{i,f} = \frac{R_{i,y_1}}{(D_{i,y_1}+R_{i,y_1})^2}\Delta_i D_f - \frac{D_{i,y_1}}{(D_{i,y_1}+R_{i,y_1})^2}\Delta_i R_f. \tag{3}$$

Then, the share of the change in the Democratic share explained by factor f is:

$$\Pi_{i,f} = \frac{\lambda_{i,f}}{\Delta_i \frac{D}{(D+R)}}. \tag{4}$$

By construction,

$$\sum_f \Pi_{i,f} \approx 1.$$

V.B. Factors' Relative Importance

We first plot the relationship between the change in the Democratic share and each factor's contribution $\lambda_{i,f}$, using one observation per unit. As shown in Figure V and in Appendix Figure D.1, the change in the Democratic share is most strongly correlated with generational turnover, adult

[17] $\Delta_i D_f$ is defined as follows for the three other factors: the number of young adults registering as Democrats minus the number of Democrats who passed away, for factor 2; the number of first-time Democratic registrants over age 25, plus the number of voters of any age re-registering as Democrats, minus the number of Democrats becoming unregistered, for factor 3; and the number of independents that became Democrats minus the number of Democrats that became independents, for factor 5. The definitions of $\Delta_i R_f$ are symmetric.

entry and exit from the electorate, and party switching between the Democratic and Republican parties, at the county level, whether we use the Catalist or TargetSmart data. The correlations for residential mobility and switches between independents and the Democratic or Republican party are also positive but weaker. Residential mobility is more strongly correlated with the change in the Democratic share at the Census Tract level (Appendix Figure D.2).

Next, we consider units trending Democratic or Republican separately and compute the overall change in the Democratic share in each group g, $\Delta_g \frac{D}{(D+R)}$. The contribution of factor f to that change and the share of the change explained by that factor are defined as:

$$\lambda_{g,f} = \frac{R_{g,y_1}}{(D_{g,y_1} + R_{g,y_1})^2} \Delta_g D_f - \frac{D_{g,y_1}}{(D_{g,y_1} + R_{g,y_1})^2} \Delta_g R_f, \tag{5}$$

$$\text{and } \Pi_{g,f} = \frac{\lambda_{g,f}}{\Delta_g \frac{D}{(D+R)}}, \tag{6}$$

where R_{g,y_1} and D_{g,y_1} are total counts of Republicans and Democrats in the group of units g in y_1, and $\Delta_g D_f$ and $\Delta_g R_f$ sum the net changes in counts of Democrats and Republicans due to factor f in units of the group.[18] By construction, we have again:

$$\sum_f \Pi_{g,f} \approx 1.$$

We proxy the shares $\Pi_{g,f}$ with:

$$\tilde{\Pi}_{g,f} = \frac{\lambda_{g,f}}{\sum_{f'} \lambda_{g,f'}},$$

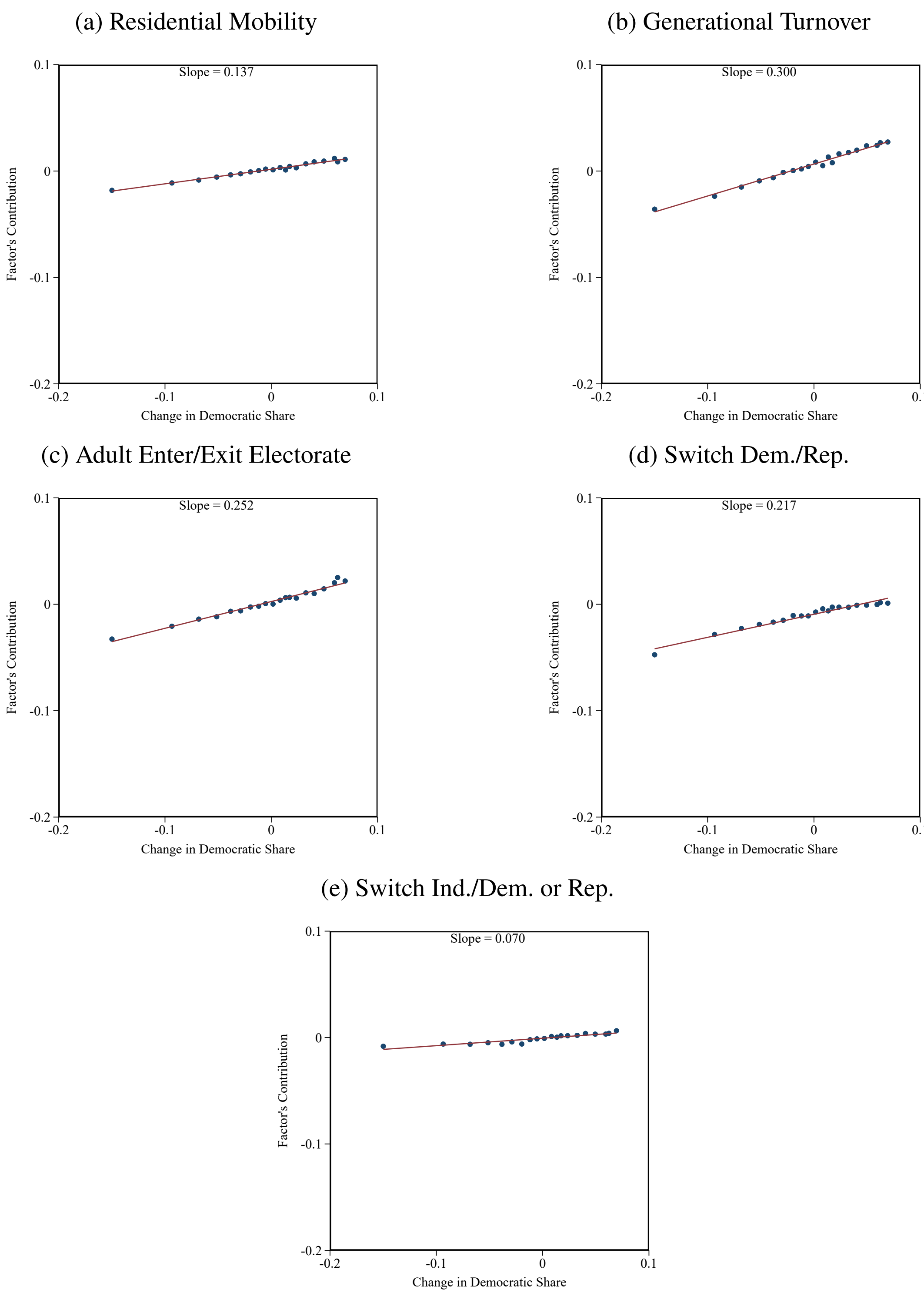
to ensure that their sum is exactly equal to 1.[19]

As shown in Figure VI, Panels A and B, the factors contributing the most to the change in the Democratic share differ substantially in counties trending Democratic and Republican. In Democratic-trending counties, the shift is primarily driven by compositional changes, with generational turnover accounting for 46.9% of the change and adult entries and exits an additional 41.5%. In Republican-trending counties, the main driver is party switching, which explains 48.6%

[18]Formally, $\Delta_g D_f = \sum_{i \in g} \Delta_i D_f$ and $\Delta_g R_f = \sum_{i \in g} \Delta_i R_f$. Democrat and Republican voters relocating across units belonging to the same group without changing their party affiliation nor their registration status do not affect these net changes.

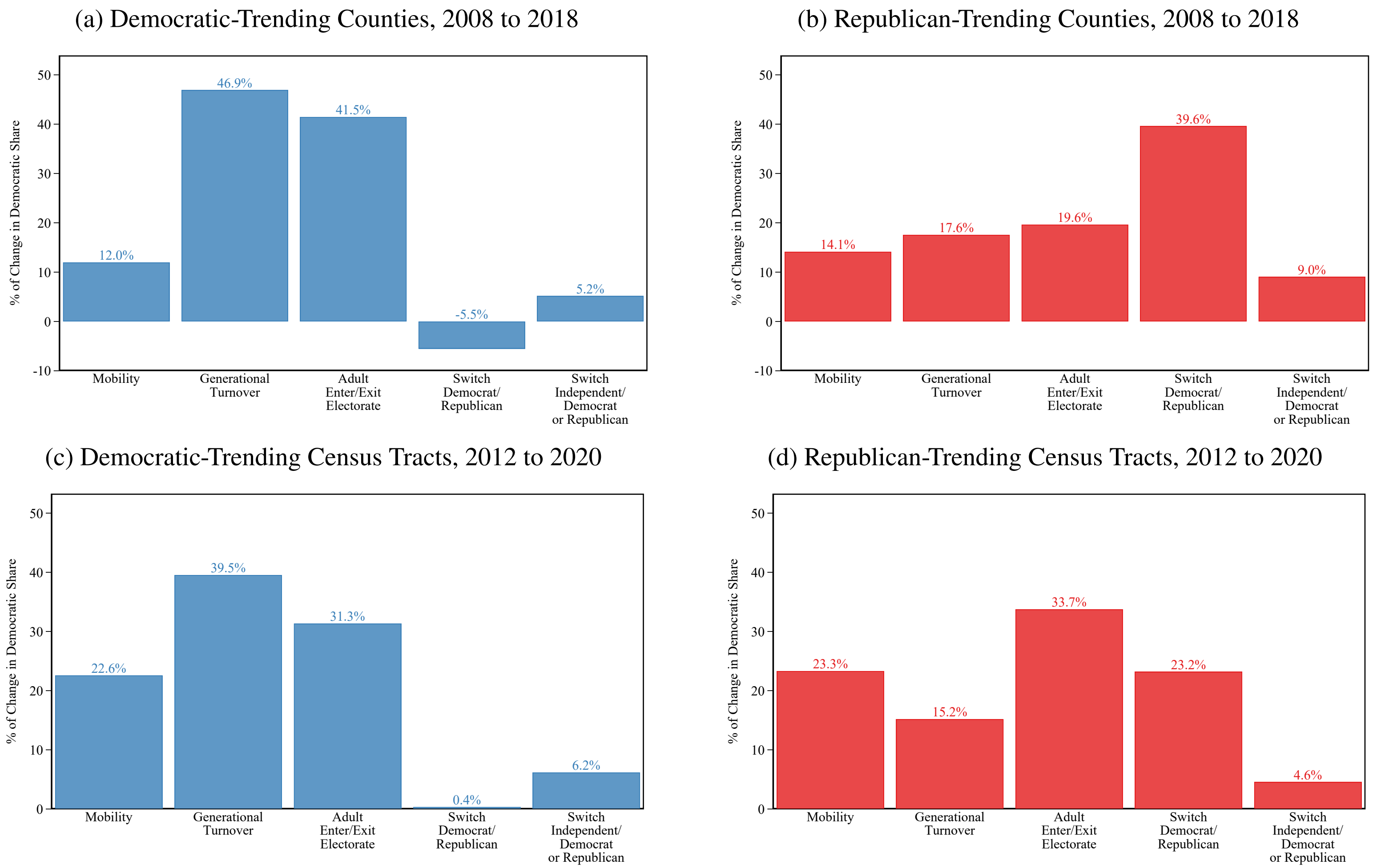
[19]As shown in Appendix Figure D.3, we obtain very similar results when plotting $\Pi_{g,f}$ instead of $\tilde{\Pi}_{g,f}$.

FIGURE V
Factors Contributing to the County-Level Change in the Democratic Share, 2008 to 2018, Catalist Data



Notes: Using 2008 and 2018 Catalist data, each binscatter plot displays the county-level relationship between the over-time change in the Democratic share (x-axis) and a decomposition factor's contribution (y-axis). The red line represents the best linear fit, estimated weighting counties by 2008 counts of registered voters.

FIGURE VI
Factors Driving Changes in the Democratic Share



Notes: Each plot shows the percentage of the change in the Democratic share explained by different decomposition factors. Panels A and B are based on 2008 and 2018 Catalist county-level data; Panels C and D are based on 2012 and 2020 TargetSmart Census Tract-level data. Samples for Panels A and C (resp. B and D) consist of Democratic-leaning (resp. Republican-leaning) geographic units; that is, geographic units that witnessed an increase (resp. a decrease) in the Democratic share over the period.

of the change in the Democratic share. This figure includes switches involving independents (9.0%) as well as switches between Democrats and Republicans (39.6%), which are doubly impactful as they each subtract a voter from one party and add them to the other. Despite widespread attention to voters expressing political homophily in their residential preferences, residential mobility only explains 12.0% and 14.1% of the change in Democratic- and Republican-trending counties. This is particularly striking given that we classify individuals who both change parties and move across counties over the sample period as movers rather than party switchers, thus biasing the decomposition toward emphasizing the role of mobility.

Figure VI, Panels C and D show the decomposition of the change in the Democratic share at the Census Tract level. That decomposition may differ from the county-level decomposition for several reasons. First, Census Tracts in which the Democratic share increases do not fully overlap with counties in which that is the case. Indeed, given the rise in geographic partisan segregation within counties visible in Figure II, it is not uncommon for Census Tracts belonging to the same county to follow opposite trends. Second, the set of individuals categorized as movers is larger at the Census Tract level since it includes not just people moving across counties but also those moving across Census Tracts of the same county. Conversely, fewer voters are classified as party switchers in the Census Tract-level analysis since that categorization requires staying within the same geographic unit. Similarly as in Democratic-trending counties, generational turnover and adult entries and exits account for most (70.8%) of the change in Democratic-trending Census Tracts. In Republican-trending Census Tracts, party switching accounts for a lower share of the change in the Democratic share than at the county level (27.8%). Residential mobility plays a slightly more important role at this level, contributing 22.6% and 23.3% of the partisan change in Democratic- and Republican-trending Census Tracts, which captures the impact of relocations across Census Tracts of the same county.[20] These differences between the county- and Census Tract-level decompositions persist when we use the 2012–2020 TargetSmart data for both (Appendix Figure D.4).

We now split counties not only by whether they trended Democratic or Republican but also by whether or not they contributed to the rise in geographic partisan segregation. As shown in Appendix Figure D.5, the share of the change in the Democratic share explained by each factor is similar in

[20]Such relocations can change group-level counts of Democrats and Republicans either if the mover also changes their party affiliation or registration status or if they move between Census Tracts that are included in two different groupings because the Democratic share increased in one and decreased in the other.

Democratic-trending counties in which partisan segregation increased (Panel A) and decreased (Panel C) as in the full set of Democratic-trending counties (Figure VI, Panel A). The same holds true for Republican-trending counties (Appendix Figure D.5, Panels B and D, and Figure VI, Panel B) and when we use TargetSmart data at the county and Census Tract levels (Appendix Figures D.6 and D.7). Furthermore, the respective contributions of the different factors to the change in the Democratic share remain similar when we focus on counties that experienced the largest change in partisan segregation (Appendix Figure D.8).[21] Once again, generational turnover explains a larger share of the change in Democratic-trending counties, switches between Democrats and Republicans play a bigger role in Republican-trending counties, and the contribution of residential mobility is modest.

Appendix Table D.2 finally reports the results of the decomposition separately for the beginning and the end of the sample: 2008–2012 versus 2012-2018 for Catalist, and 2012–2016 versus 2016–2020 for TargetSmart. In both Democratic-trending and Republican-trending areas, the contributions of the different factors to the overall change in the Democratic share are relatively stable across periods. The share of residential mobility slightly increased over time, reaching 22.0% and 13.3% (respectively 29.6% and 26.3%) in Democratic- and Republican-trending counties (resp. Census Tracts) in 2016-2020. However, the factors previously emphasized continued to dominate: the contribution of generational turnover was only slightly lower in that later period, in Democratic-trending areas, and the contribution of switches between Democrats and Republicans even larger, in Republican-trending areas.

V.C. Factors' Scale and Partisan Tilt

We take one additional step to examine the forces underlying the increase in geographic partisan segregation by noting that the contribution of each factor to the change in the Democratic share in an area depends on the interaction between two components: scale (the number of voters corresponding to the factor) and partisan tilt (the extent to which these voters trend Democratic versus Republican). For instance, in Democratic-trending areas, the contribution of generational turnover to the increase in the Democratic share may be large either because these areas count many young registrants and

[21] Specifically, we consider counties and Census Tracts whose change in the contribution to the variance of the Democratic share Δc_i, defined in equation (2), is below the 10th percentile or above the 90th percentile.

older voters passing away or because a large fraction of these areas' young registrants affiliate with the Democratic party (or a large fraction of voters passing away are Republicans). To understand why some factors matter more than others and why their relative influence differs across Democratic- and Republican-trending areas, we now define and measure the scale and partisan tilt of each factor.

For all factors except voters switching between the Democratic and Republican parties, which we turn to next, $\Delta_g D_f$ and $\Delta_g R_f$ (the net changes in counts of Democrats and Republicans due to factor f in units of group g between y_1 and y_2) can be written as:

$$\Delta_g D_f = N^I_{g,f} \times s^I_{g,f} - N^O_{g,f} \times s^O_{g,f}$$

$$\text{and } \Delta_g R_f = N^I_{g,f} \times (1 - s^I_{g,f}) - N^O_{g,f} \times (1 - s^O_{g,f}),$$

where $N^I_{g,f}$ is the total number of voters who, due to factor f, were registered either as Democrats or Republicans in a unit of group g in y_2 but not in y_1; $N^O_{g,f}$ is the number of voters who, due to factor f, were registered either as Democrats or Republicans in y_1 but not in y_2; $s^I_{g,f}$ is the share of the $N^I_{g,f}$ voters who were newly registered as Democrats rather than Republicans in y_2 due to factor f; and $s^O_{g,f}$ is the share of the $N^O_{g,f}$ voters who were no longer registered Democrats in y_2 due to factor f. For instance, when we consider the contribution of voters moving across locations to the change in the Democratic share, we count the number of voters registered as Democrats or Republicans in each area in y_2 who used to live in another area before and define $N^I_{g,f}$ as the sum of these counts across all areas in group g, and $s^D_{I,f}$ as the share of those voters registered as Democrats instead of Republicans in y_2. Plugging these expressions of $\Delta_g D_f$ and $\Delta_g R_f$ in equation (5), we obtain:

$$\lambda_{g,f} = N^I_{g,f} \times \left(\frac{R_{g,y_1}}{(D_{g,y_1} + R_{g,y_1})^2} s^I_{g,f} - \frac{D_{g,y_1}}{(D_{g,y_1} + R_{g,y_1})^2} (1 - s^I_{g,f}) \right)$$
$$- N^O_{g,f} \times \left(\frac{R_{g,y_1}}{(D_{g,y_1} + R_{g,y_1})^2} s^O_{g,f} - \frac{D_{g,y_1}}{(D_{g,y_1} + R_{g,y_1})^2} (1 - s^O_{g,f}) \right). \tag{7}$$

Equation (7) implies that affiliated voters appearing in the group's areas between y_1 and y_2 due to factor f generate a positive $\lambda_{g,f}$ and thus contribute to increasing $\frac{D}{(D+R)}$ if and only if:

$$\frac{R_{g,y_1}}{(D_{g,y_1} + R_{g,y_1})^2} s^I_{g,f} - \frac{D_{g,y_1}}{(D_{g,y_1} + R_{g,y_1})^2} (1 - s^I_{g,f}) \geq 0 \Leftrightarrow s^I_{g,f} - \frac{D_{g,y_1}}{D_{g,y_1} + R_{g,y_1}} \geq 0.$$

Similarly, affiliated voters disappearing from the area contribute to increasing $\frac{D}{(D+R)}$ if and only if:

$$\frac{R_{g,y_1}}{(D_{g,y_1}+R_{g,y_1})^2}s^O_{g,f} - \frac{D_{g,y_1}}{(D_{g,y_1}+R_{g,y_1})^2}(1-s^O_{g,f}) \leq 0 \Leftrightarrow s^O_{g,f} - \frac{D_{g,y_1}}{D_{g,y_1}+R_{g,y_1}} \leq 0.$$

Intuitively, $\frac{D}{(D+R)}$ increases if there are relatively more Democrats appearing in the area and relatively fewer Democrats disappearing from the area than the baseline fraction of Democrats. Therefore, to disentangle the role of scale and partisan tilt in the contribution of each factor to the change in the Democratic share, we measure $N^I_{g,f}$ and $N^O_{g,f}$ on one hand, and $s^I_{g,f} - \frac{D_{y_1}}{D_{y_1}+R_{y_1}}$ as well as $s^O_{g,f} - \frac{D_{y_1}}{D_{y_1}+R_{y_1}}$ on the other hand.

For voters switching between the Democratic and Republican parties, $\Delta_g D_f$ and $\Delta_g R_f$ are defined as follows:

$$\Delta_g D_f = -\Delta_g R_f = s^{R\to D}_g R_{g,y_1} - s^{D\to R}_g D_{g,y_1},$$

with $s^{R\to D}_g$ the share of voters initially registered as Republicans who become Democrats, and $s^{D\to R}_g$ the share of voters initially registered as Democrats who become Republicans. Plugging these expressions in equation (5), we obtain that, for this factor:

$$\lambda_{g,f} = \frac{s^{R\to D}_g R_{g,y_1} - s^{D\to R}_g D_{g,y_1}}{R_{g,y_1}+D_{g,y_1}}, \tag{8}$$

and $\lambda_{g,f}$ is positive if and only if:

$$\frac{s^{R\to D}_g}{s^{R\to D}_g + s^{D\to R}_g} - \frac{D_{g,y_1}}{D_{g,y_1}+R_{g,y_1}} \geq 0.$$

Therefore, for this factor, we disentangle the role of scale and partisan tilt by measuring the number of switches between Democrats and Republicans $N^{D\leftrightarrow R}_g$ on one hand and $\frac{s^{R\to D}_g}{s^{R\to D}_g+s^{D\to R}_g} - \frac{D_{g,y_1}}{D_{g,y_1}+R_{g,y_1}}$ on the other hand.

The results of this decomposition, shown in Table III, first reveal that the scales of the different factors are comparable in Democratic-trending and Republican-trending counties. The largest difference is for the number of switches between Democrats and Republicans, which correspond to 1.9% of the initial count of registrants in Democratic-trending counties and 2.9% in Republican-trending counties.

Second, the partisan tilt of most factors contributes to increasing the Democratic share, in the first set of counties, and to decreasing it in the second. Most coefficients are positive in column 3 and negative in column 4, indicating that, in Democratic-trending counties, the share of new Democrats among voters corresponding to a specific factor is larger than the baseline fraction of Democrats, and that the fraction of Democrats among disappearing voters corresponding to that factor is lower than the baseline fraction. Conversely, most coefficients are negative, in column 7, and positive, in column 8, corresponding to Republican-trending counties. The behavior for which we observe the largest divergence from the overall trend is party switching, in Democratic-trending counties: in these counties, switches from the Democrats to the Republicans dominate switches in the opposite direction, working against the overall increase in the Democratic share.

Third, the partisan tilt is particularly strong for generational turnover, in Democratic-trending counties. In these counties, new voters are 11.9 percentage points more likely to be Democrats than the baseline fraction of Democrats. In Republican-trending counties, the partisan tilt is much lower for generational turnover (new voters are only 2.8 percentage points more likely to be Republicans than the baseline fraction of Republicans) but it is much stronger for switches between Democrats and Republicans (28.7 points, against -3.7 points in Democratic-trending counties).

We obtain similar results when using the TargetSmart data at the county and Census Tract levels (Appendix Tables D.3 and D.4) and when also splitting counties by whether or not they contributed to the rise in geographic partisan segregation or running the decomposition separately for the beginning and the end of the sample (Appendix Tables D.5 and D.6). Overall, the differences in factors' relative importance in Democratic- and Republican-trending areas visible in Figure VI reflect differences in partisan tilt more than in scale.

TABLE III

COUNTY-LEVEL FACTORS' SCALE AND PARTISAN TILT, 2008 TO 2018, CATALIST DATA

	Democratic-Trending Counties				Republican-Trending Counties			
	$N^{I}_{g,f}$	$N^{o}_{g,f}$	$s^{I}_{g,f}$ - $D_{y1}/(D_{y1} + R_{y1})$	$s^{O}_{g,f}$ - $D_{y1}/(D_{y1} + R_{y1})$	$N^{I}_{g,f}$	$N^{o}_{g,f}$	$s^{I}_{g,f}$ - $D_{y1}/(D_{y1} + R_{y1})$	$s^{O}_{g,f}$ - $D_{y1}/(D_{y1} + R_{y1})$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mobility	4,136,664	4,702,999	0.039	-0.001	4,454,969	4,124,818	-0.109	-0.054
Gen. Turnover	5,333,991	3,564,926	0.119	-0.003	4,163,081	3,804,141	-0.028	0.055
Adult Enter/Exit Electorate	6,458,566	6,860,263	0.091	0.003	5,005,425	5,986,077	-0.051	0.019
Switch Dem./Rep.	988,116		-0.037		1,354,805		-0.287	
Switch Ind./Dem. or Rep.	1,803,636	1,677,077	0.0003	-0.042	1,377,226	1,139,814	-0.094	0.035
Baseline Registrants Counts	52,845,103				46,394,551			

Notes: The table is based on the Catalist data. For each decomposition factor (in rows), the table disaggregates the factor's contribution to the 2008-to-2018 county-level change in the Democratic share between the factor's scale (columns 1-2 and 5-6) and partisan tilt (columns 3-4 and 7-8). Columns 1-4 refer to counties that became more Democratic between 2008 and 2018, while columns 5-8 refer to counties that became more Republican over the same period.

VI. CHANGES IN PARTISAN SEGREGATION AND DEMOGRAPHIC GROUPS

We finally exploit the fact that we observe each voter's demographic characteristics, in addition to their location and party affiliation, to compare the change in partisan segregation among voters of different genders, ages, and races, and assess the contribution of these different groups to the decomposition presented in Section V.

VI.A. Changes in Partisan Segregation by Demographic Group

In each county and Census Tract, we first restrict the sample to voters of a specific gender, age quartile, or race, and compute the Democratic share at the beginning and at the end of the period for each of these groups.[22] As shown in Appendix Figures E.1 and E.2, the county- and Census Tract-level distributions of the Democratic share have widened over time for men, women, as well as voters of each age quartile. The standard deviation of the Democratic share increased more for voters in the first and second age quartiles than those in the third and fourth quartiles, indicating that geographic partisan segregation grows faster among younger cohorts (Appendix Table E.1).[23] It rose to a similar extent for men and women (Appendix Table E.2). In contrast, Figure VII and Appendix Table E.3 show that white voters are the only racial group that experienced an increase in partisan segregation. This trend was accompanied by a shift in the distribution of the Democratic share to the left, indicating greater Republican homogeneity. Partisan segregation decreased among Blacks, Hispanics, and voters of other races at both the county and Census Tract levels.[24]

VI.B. Contribution of Demographic Groups to the Factors' Decomposition

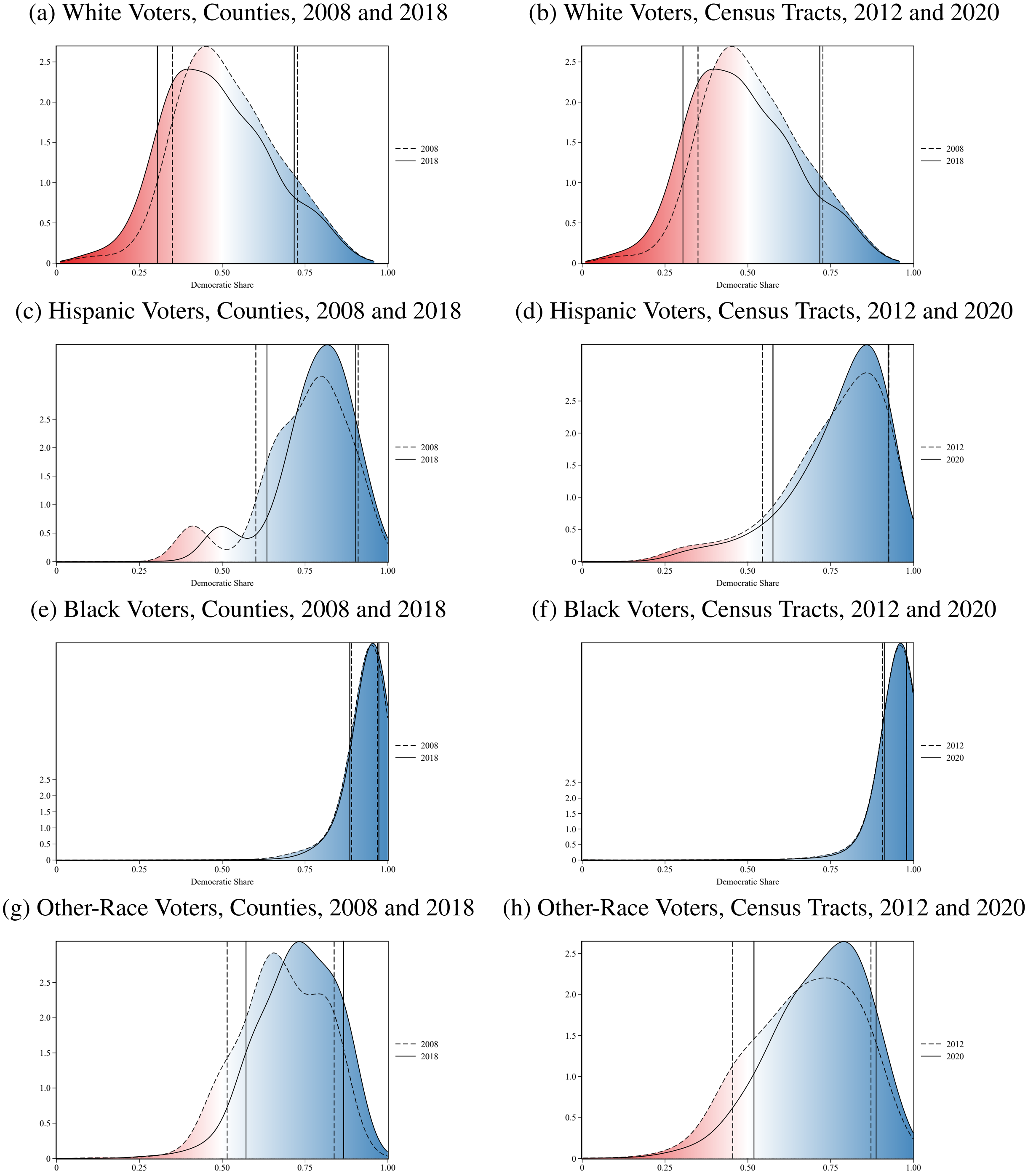
We now go back to the decomposition of the change in the Democratic share in Democratic- and Republican-trending areas into residential mobility, generational turnover, entry and exit of adult

[22] Age quartiles are defined based on voters' age in the first year of the dataset (2008 in Catalist and 2012 in TargetSmart), if they were already registered on the voter rolls then, and based on their age at the time at which they first registered, if they registered afterward.

[23] Between 2008 and 2018, the standard deviation of the county-level Democratic share measured using the Catalist data increased by 8.1% (0.173/0.160), 8.2%, 4.8%, and 2.9% for voters in the first, second, third, and fourth quartiles.

[24] The distributions of the Democratic share shifted to the right for Hispanics and voters of other races. For Black voters, the distributions were already centered around very high values of Democratic homogeneity at the beginning of the period and they did not change much over time.

FIGURE VII
Distribution of the Democratic Share by Race



(a) White Voters, Counties, 2008 and 2018

(b) White Voters, Census Tracts, 2012 and 2020

(c) Hispanic Voters, Counties, 2008 and 2018

(d) Hispanic Voters, Census Tracts, 2012 and 2020

(e) Black Voters, Counties, 2008 and 2018

(f) Black Voters, Census Tracts, 2012 and 2020

(g) Other-Race Voters, Counties, 2008 and 2018

(h) Other-Race Voters, Census Tracts, 2012 and 2020

Notes: We show kernel density plots of the race-specific Democratic share. All kernel density estimates are weighted by race-specific counts of registered voters in a given county-year and use a Gaussian kernel with bandwidth of 0.05. In each plot, vertical lines represent the 10th (vertical lines on the left tail of each plot) and 90th percentiles (vertical lines on the right tail of each plot). Panels A, C, E, and G use the county-level Catalist data for the 2008 and 2018 elections. Panels B, D, F, and H use the Census Tract-level TargetSmart data for the 2012 and 2020 elections.

voters, and changes in partisanship, and assess the contribution of voters of different genders, ages, and races to each of these factors.

We split $\lambda_{g,f}$, the contribution of factor f to the change in the Democratic share in the units of group g, into contributions of different demographic groups d:

$$\lambda_{g,f,d} = \frac{R_{g,y_1}}{(D_{g,y_1} + R_{g,y_1})^2}\Delta_{g,d}D_f - \frac{D_{g,y_1}}{(D_{g,y_1} + R_{g,y_1})^2}\Delta_{g,d}R_f, \tag{9}$$

where $\Delta_{g,d}D_f$ and $\Delta_{g,d}R_f$ sum the net changes in counts of Democrats and Republicans among demographic group d due to factor f.[25]

Then, the share of the change in the Democratic share explained by that factor and demographic group is:

$$\Pi_{g,f,d} = \frac{\lambda_{g,f,d}}{\Delta_g \frac{D}{(D+R)}}, \tag{10}$$

which, similarly as for $\Pi_{g,f}$, we proxy with:

$$\tilde{\Pi}_{g,f,d} = \frac{\lambda_{g,f,d}}{\sum_{f'}\sum_{d'}\lambda_{g,f',d'}}.$$

We report the results of the county-level decomposition using Catalist data in Table IV.[26] In Democratic-trending counties, the increase in the Democratic share is primarily driven by young voters, women, and non-white voters. Generational turnover accounts for 46.9% of that increase, as established in Section V, with up to 97.0% (45.5/46.9) of this contribution coming from voters in the first age quartile. Indeed, the share of young voters registering as Democrats rather than Republicans in these areas is much higher than the already high baseline Democratic share (73.6% against 61.7%). The contribution of generational turnover is also driven disproportionately by female, Black, Hispanic, and other race voters, relative to their shares in the electorate (68.2, 23.2, 39.9, and 17.7%

[25]Formally, $\Delta_{g,d}D_f = \sum_{i\in g}\Delta_{i,d}D_f$ and $\Delta_{g,d}R_f = \sum_{i\in g}\Delta_{i,d}R_f$, where $\Delta_{i,d}D_f$ and $\Delta_{i,d}R_f$ denote net changes in counts of Democrats and Republicans among voters of demographic group d in unit i due to factor f. Also note that R_{g,y_1} and D_{g,y_1} are defined as before as total counts (that are not demographic group specific) of Republicans and Democrats in the group of units g in y_1, to ensure that $\sum_d \lambda_{g,f,d} = \lambda_{g,f}$.

[26]Results from the county- and Census Tract-level decompositions using TargetSmart data, shown in Appendix Tables E.4 and E.5, are qualitatively similar. Panels B and C of these tables and of Table IV do not show the $\tilde{\Pi}_{g,f,d}$'s of voters with missing age or gender information, so vertical sums within these panels only add up to a given factor's overall contribution reported in Panels A up to an error term due to these voters. Instead, voters with missing race are included in the "Other race" category, so vertical sums within Panels D perfectly add up to factors' overall contribution.

TABLE IV

DEMOGRAPHIC GROUPS' CONTRIBUTION TO FACTORS DRIVING COUNTY-LEVEL CHANGES IN THE DEMOCRATIC SHARE, 2008 TO 2018, CATALIST DATA

	Democratic-Trending Counties						Republican-Trending Counties					
		Factors						Factors				
	% Voters	Mobility	Gen. Turnover	Adult Enter/ Exit Electorate	Switch Dem./ Rep.	Switch Ind./ Dem. or Rep.	% Voters	Mobility	Gen. Turnover	Adult Enter/ Exit Electorate	Switch Dem./ Rep.	Switch Ind./ Dem. or Rep.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Panel A. Overall Contribution						Panel A. Overall Contribution					
		12.0	46.9	41.5	-5.5	5.2		14.1	17.6	19.6	39.6	9.0
	Panel B. By Age Quartile						Panel B. By Age Quartile					
Aged 18-27 (Q1)	20.4	5.2	45.5	5.0	0.8	2.4	18.8	2.2	6.5	3.2	3.6	1.1
Aged 28-42 (Q2)	26.4	1.6	-0.6	16.8	-1.4	1.4	24.6	3.5	0.4	3.3	9.5	2.9
Aged 43-57 (Q3)	25.2	3.2	-1.3	6.7	-1.6	1.2	25.3	4.4	1.8	5.5	12.8	2.5
Aged 58+ (Q4)	28.0	1.9	3.5	9.7	-3.5	0.1	31.3	4.0	8.7	6.5	13.7	2.5
	Panel C. By Sex						Panel C. By Sex					
Male	46.1	6.7	13.6	16.8	-3.6	2.0	46.6	7.8	12.5	10.3	19.2	5.0
Female	53.9	5.2	32.0	23.8	-1.9	3.2	53.4	6.3	5.1	9.3	20.4	4.1
	Panel D. By Race						Panel D. By Race					
Black	11.6	-0.7	10.9	2.8	1.0	1.4	7.9	-0.6	-6.0	0.4	-0.2	-0.5
Hispanic	13.3	0.2	18.7	13.7	0.9	1.2	3.9	-0.01	-3.6	-2.8	0.4	-0.2
White	67.9	11.9	9.0	17.0	-7.8	1.4	85.9	14.6	28.3	22.7	39.1	9.8
Other race	7.2	0.6	8.3	7.9	0.4	1.1	2.3	0.1	-1.2	-0.6	0.4	-0.04

Notes: The table is based on the Catalist data. Panel A reports the share of the change in the Democratic share attributable to each decomposition factor, separately for counties that became more Democratic (columns 1-6) or more Republican (columns 7-12) between 2008 and 2018. Each cell in Panels B, C, and D shows how much a given demographic group (in rows) contributed to a given factor's share of the decomposition (in columns). Vertical sums within panels add up to a given factor's overall contribution reported in Panel A, up to an error term due to voters with missing age or gender information (voters with missing race are instead included in the "Other race" category). For example, generational turnover explains 46.9% of the change in the Democratic share in counties that became more Democratic; 10.9, 18.7, 9.0, and 8.3 percentage points of this 46.9% are due to, respectively, Black, Hispanic, White, and other-race voters (i.e., 10.9% + 18.7% + 9.0% + 8.3% = 46.9%). Columns 1 and 7 report the fractions of voters belonging to each demographic group in 2008.

against 53.9, 11.6, 13.3, and 7.2%). The contribution of the second main factor responsible for the increase in the Democratic share, adult entries and exit, is also primarily driven by women and racial and ethnic minority voters.

In Republican trending counties, the drop in the Democratic share is primarily driven by white and older voters instead. Party switching, the main factor in these counties, is relatively rare among younger voters but is contributed to relatively equally by voters in older age groups. Most strikingly, white voters explain 98.8% of that factor's contribution (39.1/39.6). White voters also account for most of the contribution of switches between independents and either major party, adult entries and exits, and generational turnover. Instead, minority groups often go *against* the main trend. In particular, the propensity of young Blacks, Hispanics, and voters of other races to affiliate with the Democratic Party when they first get registered results in these groups lowering the net contribution of generational turnover to the decline in the Democratic share. Men and women explain a similar share of the contributions of the different factors except for generational turnover, which is primarily driven by men.

For all the differences observed between demographic groups' contributions to partisan change in Democratic-trending and Republican-trending areas, one pattern is common: in both types of areas, the contribution of residential mobility to the change in the Democratic share is almost exclusively driven by white voters. It is much more common for white voters to relocate to counties whose partisan composition is better aligned with their own party affiliation than it is for minority voters.

VII. CONCLUSION

Until recently, the only available over-time data on the partisan leanings of the electorate were vote shares and counts of Republicans and Democrats aggregated at coarse geographic levels. As a consequence, while scholars found evidence of geographic partisan clustering in the U.S., first-order questions on the causes and extent of this phenomenon remained unanswered. Our individual-level panel data tracking the location and party affiliation of all U.S voters from 2008 to 2020 enable us to offer the richest evidence on changes in geographic partisan segregation yet presented.

We show that segregation increases substantially not just across Congressional Districts and counties, but also across small neighborhoods within these larger units, and we uncover the forces responsible for this trend.

Voters fleeing supporters of the opposite party and choosing where to live based on politics could be a symptom of growing partisan discord. However, while such sorting exists, it is a minor driver of changes in political geography. In Democratic-trending places, the most impactful factors are influxes of new Democratic-leaning young voters and older first-time registrants replacing voters who are dying or de-registering. In Republican areas, the most prominent factor driving partisan segregation is partisan realignment, with voters leaving the Democratic party and registering as Republicans.

Our results still offer reasons for concern. To the extent that peers' influence on children and adults is the reason why new voters and party switchers disproportionately embrace the dominant party affiliation, partisan segregation is likely to perpetuate itself. In fact, we see it increasing systematically year-over-year, and more rapidly among younger than older voters.

Furthermore, Democratic- and Republican-trending areas show stark differences in average income and education levels, age and race compositions, and even the types of voters driving the rise in partisan homogeneity: youths, women, and non-white voters on the one hand, and white and older voters on the other hand. Thus, growing partisan segregation exacerbates the confluence of geographic, demographic, and political divides in the United States. Far from uncovering cross-cutting cleavages capable of promoting compromise and enhancing democratic resilience, our results offer the picture of an increasingly divided country.

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Online Appendix to "Sources and Extent of Rising Partisan Segregation in the U.S. – Evidence from 143 Million Voters" (Brown, Cantoni, Enos, Pons, and Sartre)

A. The Catalist and TargetSmart Data

A.1. Processing the Catalist Data

Here, we detail the steps that we used to 1) de-duplicate the Catalist data and 2) create the datasets used for county- and Census Tract-level analyses based on these data. A description of the Catalist data can be found in Cantoni and Pons (2022) and this subsection is partly reproduced from that paper's appendix.

A.1.1. De-duplicating the Catalist Data

The information Catalist shares with its clients usually stems from a cross-sectional "live file," containing the present-day location and the full voter turnout history of every individual who ever appeared in its database. However, Catalist has also been saving "historical files": snapshots of its live file as of the date of each biennial federal election. We received six historical files, corresponding to the 2008, 2010, 2012, 2014, 2016, and 2018 nationwide elections, and matched them with the current live file. The historical files constitute our source of longitudinal information on voter residence, and the live file our source of longitudinal information on voter behavior.

Because our version of the Catalist data includes individual voter identifiers but no individual name or address, we rely on the work done by Catalist to de-duplicate the data and to match observations corresponding to the same voter across states and over time. Specifically, when a voter is observed moving across states, Catalist creates a new record and updates the original record instead of erasing it. Consequently, the Catalist database is uniquely identified by voter ID and state. After using voter ID and state to match the historical files with the live file, we de-duplicate the matched historical files on voter ID, using the following lexicographic rules.

1. We privilege the record corresponding to the state where a voter voted, if any;
2. followed by records flagged as "best state" by Catalist;
3. then we use voter registration, privileging voter registration statuses in this order: "active," "moved, unregistered" (voters who, according to the National Change of Address or commercial data, have moved into the state, but did not re-register in that state), "unregistered" (individuals

who do not appear on current or past voter files but are known to reside in the state), "inactive," and "dropped" (individuals who appeared on past state voter files, but not in the most recent one);

4. then the record with the oldest registration date;

5. finally, among residual duplicates, we keep a reproducibly random record.

A.1.2. Preparing the Catalist County-level Analysis Data

To create the dataset used for county-level analyses, we begin by imputing missing county FIPS codes using both forward and backward values, but only when these values are identical for the same voter. For example, if a voter has a missing county FIPS code in 2012 but non-missing identical county FIPS codes in 2010 and 2014, we assign the 2010 and 2014 county FIPS code to the missing value in 2012.

We then flag observations meeting any of the following criteria:

- observations missing a county FIPS code after the aforementioned imputation step;
- observations whose county FIPS code is not part of the list of county FIPS codes appearing in the Decennial Census (the 2000 Decennial Census, for observations between 2008 and 2014, and the 2010 Decennial Census, for observations in 2016 and 2018);
- observations whose county FIPS code conflicts with their state identifier;
- and observations corresponding to counties that were redrawn during the sample period.

We conservatively drop all observations corresponding to voters with at least one flagged observation. In addition, we exclude several sparsely populated Alaskan county equivalents which were divided into multiple counties between 2008 and 2018. We proceed that way as it is unclear whether the county FIPS codes for individuals in the original counties changed due to relocation or due to reassignment to new counties without moving. We also drop Broomfield County, Colorado (FIPS code 08-014), as Catalist only began using its FIPS code after 2008, and Mono county, California (FIPS code 06-051), due to apparent inconsistencies in voter partisanship classification.

For example, in Mono County, Democratic and Republican voter party affiliation appear "inverted" in at least one year.[27]

A.1.3. Preparing the Catalist Census Tract-level Analysis Data

To create the dataset used for Census Tract-level analyses, we first flag observations meeting any of the following criteria:

- observations missing a Census Tract FIPS code;
- observations whose Census Tract FIPS code is not part of the list of Census Tract FIPS codes appearing in the Decennial Census;
- and observations whose Census Tract FIPS code conflicts with their county and state identifiers.

We then impute the Census Tract FIPS code of these flagged observations. For example, if a voter has a missing Census Tract FIPS code in 2012 but non-missing and non-flagged identical Census Tract FIPS codes in 2010 and 2014, we assign the 2010 and 2014 Census Tract FIPS code to the missing value in 2012. The detailed steps of the procedure we use to impute missing values are as follows:

1. If lagged and forward observations have identical, non-flagged Census Tract FIPS codes, we use that code to replace the Census Tract FIPS code for the current, flagged observation.
2. If only the lagged observation is non-flagged, we replace the flagged current observation's Census Tract FIPS code with the lag's, provided that both observations are in the 2008–2014 or in the 2016–2018 ranges. We do so because Catalist uses Census Tract identifiers from the 2000 Decennial Census for the years 2008–2014 and Census Tract identifiers from the 2010 Decennial Census for 2016 and 2018.
3. If only the forward observation is non-flagged, we use its Census Tract FIPS code to replace the flagged current observation's if the lead and the current observation are both either in the 2008–2014 or in the 2016–2018 range.

[27] Unlike in the Catalist data, we retain the Alaskan county equivalents, Broomfield County, Colorado, and Mono County, California while using the TargetSmart data. Indeed, in that dataset, each of these counties' addresses is consistently assigned to the same county and Census Tract across all years, and we do not observe any inconsistencies in the classification of voter partisanship over time.

4. If the current flagged observation is in 2016 or 2018, and the lagged observation is from 2014 or earlier, then:
   - We replace the flagged observation with the 2010 Census Tract FIPS code associated with the lagged observation,
   - But only if the lagged observation is non-flagged and the 2000 Census Tract it is located in corresponds to only one 2010 Census Tract.
5. If the current flagged observation is in 2014 or earlier, and the lead observation is from 2016 or later, then:
   - We replace the flagged observation with the 2000 Census Tract FIPS code associated with the lead observation,
   - But only if the lead observation is non-flagged and the 2010 Census Tract it is located in corresponds to only one 2000 Census Tract.

Finally, we flag voters meeting any of the following criteria:

- they have at least one remaining flagged observation whose Census Tract FIPS code could not be imputed;
- they reside in counties with a single Census Tract;[28]
- or they were previously flagged at the county level.[29]

We conservatively drop all observations corresponding to these flagged voters.

A.2. Processing the TargetSmart Data

Here, we detail the steps that we used to 1) further de-duplicate the TargetSmart data relative to what was already done by TargetSmart and 2) build on TargetSmart's work to identify movers. The

[28] This step ensures the valid computation of the two-party Index of Dissimilarity, as our main analysis uses Census Tracts as subunits.

[29] This final step is motivated by the fact that uncertainty in county-level identification reduces confidence in individuals' assignment to finer geographic units and may compromise the validity of the index of Dissimilarity at the county level. Accordingly, voters included in the Census Tract-level dataset are a strict subset of those included in the county-level dataset.

description of the TargetSmart data processing was developed in Brown et al. (2023), and this section is largely reproduced from that paper's appendix.

A.2.1. Initial TargetSmart Data Cleaning and De-duplication

TargetSmart provides a "voterbase ID" field (henceforth VBID) that uniquely identifies a row in the data for a given state and year. TargetSmart also provides an "exact track ID" (henceforth ETID), which represents its efforts to link individuals *across* states and years. We use this information together with individuals' first name, middle name, last name, date of birth, and vote history to de-duplicate the TargetSmart data, so that for each voter and year the record used in the analysis is the most likely current record. We also use this information to build on TargetSmart's linkage model and further link voters across states and years.

First, we take the following steps to clean the raw TargetSmart files:

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

2. Use TargetSmart's information from the United States Postal Service National Change of Address database to drop voters that no longer reside at their listed residence.

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

4. Recode invalid ZIP codes and Census IDs as missing.

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

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

A.2.2. De-duplicating the TargetSmart Data within States

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

1. Assume that records that share a VBID are the same person, and assign them the same SUID. However, if the same VBID has been assigned to two rows where the first name, last name, and date of birth are *all* different, or where the maximum difference in birth year is more than five years *and* the month and day of birth are different too, then break this link.
2. Drop individuals with a SUID that is never associated with a name or date of birth.
3. Group by ETID.
    - Case 1: If *at least one* of the first name, last name, and DOB are the same among all members of the group, there is only one record per year, and the maximum age difference is less than or equal to five years, then assign all rows the same SUID.
    - Case 2: If not everyone in the group shares *either* a first name, last name, or DOB, group them by name and DOB and – as long as there is only one record per year – assign rows within each group the same SUID.
4. For records that are unique *within a year* by first name, last name, and DOB, group records by these variables and assign them the same SUID.
5. For records that are unique *within a year* by first name, middle name, last name, and DOB, group records by these variables and assign them the same SUID.

A.2.3. De-duplicating the TargetSmart Data across States

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

1. Drop rows missing first name, last name, or DOB.

2. Split the DOB field into year, month, and day. If the DOB ends in "01," set the DOB day to missing. If the DOB ends in "0101," set the DOB month and day to missing.[30]

3. Group by ETID and check that the maximum vote count for any election is 1. If so, assign these rows the same UID.

4. Group by first name, last name, and year, month, and day of birth. Ensure that:

   - Each record has non-missing information for all of the grouping variables.
   - Each record is uniquely identified by these variables within state.
   - The group has a record from at least two states.
   - The records do not have different middle initials.
   - The maximum vote count among records in the group for any election is one.

   If so, assign these rows the same UID.

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

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

A.3. Comparison between the Catalist and TargetSmart data

Table A.1 provides year-by-year comparisons of summary statistics in states recording partisan registration between the Catalist and TargetSmart data. The TargetSmart and Catalist numbers are based on the data processed following the steps outlined above. Catalist adopted 2010 Census Tract

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

FIPS codes starting in 2016, explaining the sharp increase in counts of Census Tracts between 2014 and 2016. In contrast, TargetSmart uses 2010 Census Tract codes throughout the 2012-2020 panel.

Table A.1 Summary Statistics, Catalist and TargetSmart Data

	Catalist (1)	TargetSmart (2)
Panel A. 2008		
States	30	-
Counties	1,373	-
Census Tracts	36,541	-
Registered voters	99,239,654	-
Share Democrat	0.435	-
Share Republican	0.305	-
Share Black	0.099	-
Share Hispanic	0.089	-
Share white	0.763	-
Share male	0.461	-
Panel B. 2010		
States	30	-
Counties	1,373	-
Census Tracts	36,532	-
Registered voters	97,234,739	-
Share Democrat	0.428	-
Share Republican	0.305	-
Share Black	0.100	-
Share Hispanic	0.093	-
Share white	0.756	-
Share male	0.461	-
Panel C. 2012		
States	30	30
Counties	1,373	1,378
Census Tracts	36,543	40,944
Registered voters	100,387,678	84,797,031
Share Democrat	0.419	0.420
Share Republican	0.300	0.303
Share Black	0.104	0.089
Share Hispanic	0.100	0.092
Share white	0.742	0.763
Share male	0.461	0.461
Panel D. 2014		
States	30	30
Counties	1,373	1,380
Census Tracts	36,544	41,015
Registered voters	100,266,211	88,916,458
Share Democrat	0.412	0.415
Share Republican	0.296	0.297
Share Black	0.106	0.089
Share Hispanic	0.104	0.096
Share white	0.734	0.755
Share male	0.462	0.463

(continued)

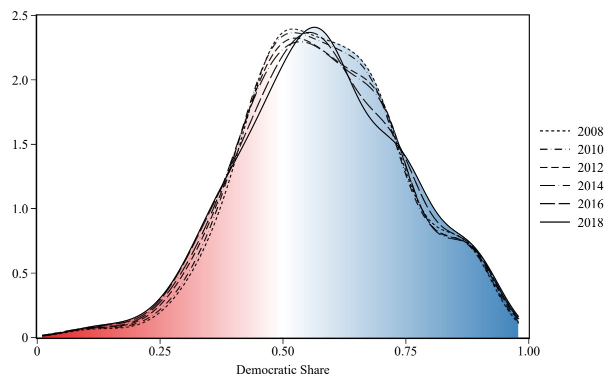
	Catalist (1)	TargetSmart (2)
Panel E. 2016		
States	30	30
Counties	1,373	1,380
Census Tracts	41,010	41,020
Registered voters	106,278,208	92,171,092
Share Democrat	0.411	0.415
Share Republican	0.296	0.299
Share Black	0.105	0.089
Share Hispanic	0.114	0.102
Share white	0.720	0.746
Share male	0.463	0.462
Panel F. 2018		
States	30	30
Counties	1,373	1,380
Census Tracts	41,074	41,022
Registered voters	107,182,121	95,770,825
Share Democrat	0.404	0.406
Share Republican	0.290	0.292
Share Black	0.105	0.087
Share Hispanic	0.120	0.111
Share white	0.709	0.735
Share male	0.463	0.462
Panel G. 2020		
States	-	30
Counties	-	1,380
Census Tracts	-	41,024
Registered voters	-	103,676,124
Share Democrat	-	0.409
Share Republican	-	0.295
Share Black	-	0.085
Share Hispanic	-	0.118
Share white	-	0.723
Share male	-	0.460

Notes: The table reports year-specific summary statistics of comparable variables from the Catalist (column 1) and the TargetSmart datasets (column 2) used for county-level analyses. For both datasets, the sample is restricted to registered voters in the 29 states plus DC that record party affiliation in every general election, 2008-2020.

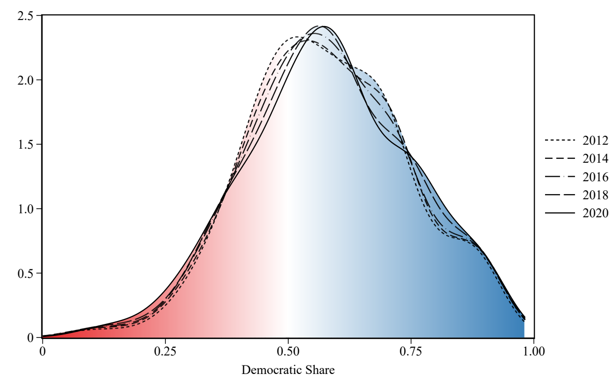
B. Changes in Geographic Partisan Segregation, Additional Figures and Tables

Figure B.1 Distribution of the County- and Census Tract-Level Democratic Share, All Years, Catalist and TargetSmart Data

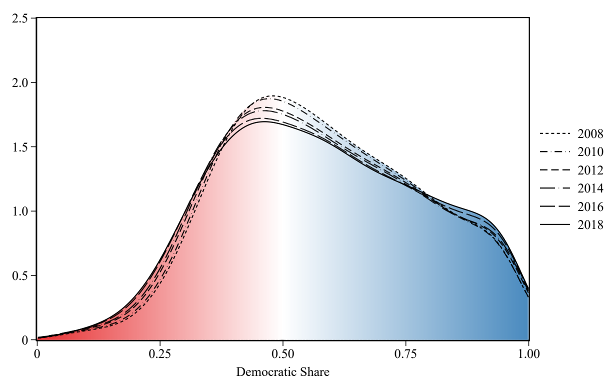
(a) Counties, 2008 to 2018, Catalist Data



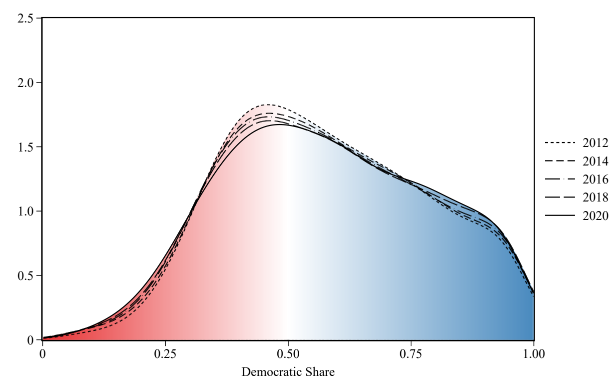
(b) Counties, 2012 to 2020, TargetSmart Data



(c) Census Tracts, 2008 to 2018, Catalist Data



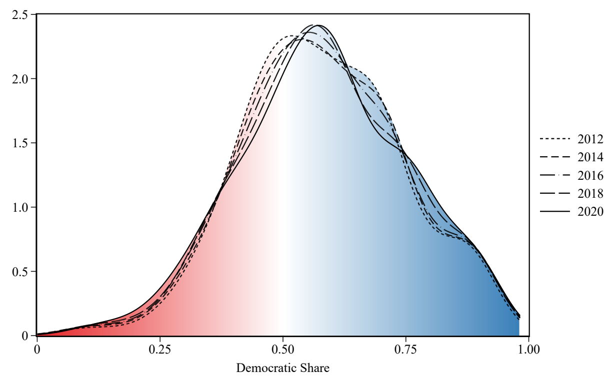
(d) Census Tracts, 2012 to 2020, TargetSmart Data



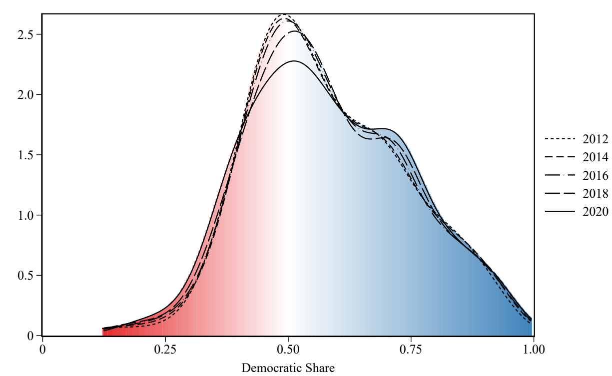
Notes: The figure plots kernel density estimates of the Democratic share at the county and Census Tract levels. Panels A and C use Catalist data for the 2008–2018 elections. Panels B and D use TargetSmart data for the 2012–2020 elections. All kernel density estimates are weighted by counts of registered voters in a given Census Tract-year and use a Gaussian kernel with bandwidth of 0.05.

Figure B.2 Distribution of the Democratic Share, All Years and Geographic Levels, TargetSmart Data

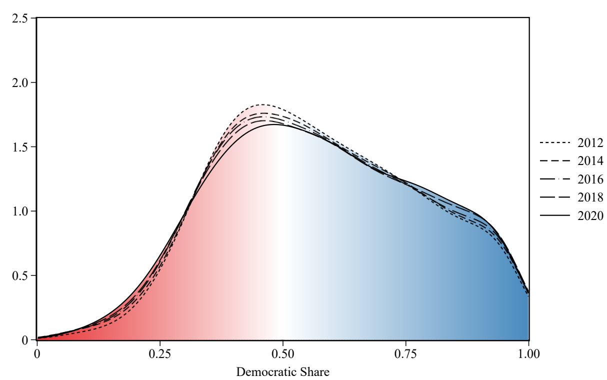
(a) Counties, 2012 to 2020



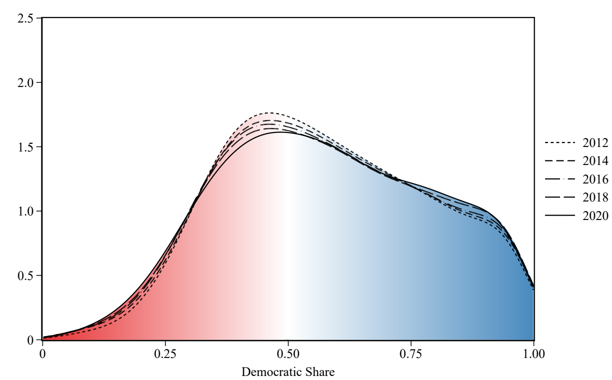
(b) Congressional Districts, 2012 to 2020



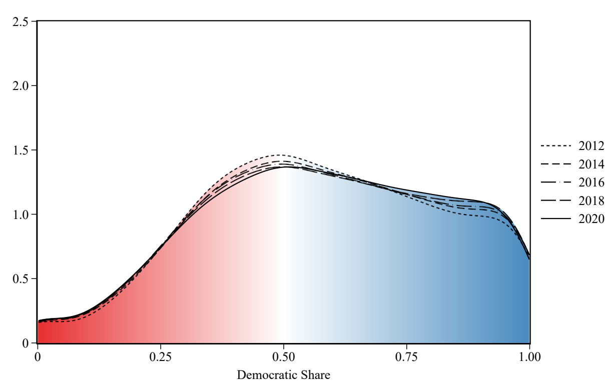
(c) Census Tracts, 2012 to 2020



(d) Census Block Groups, 2012 to 2020



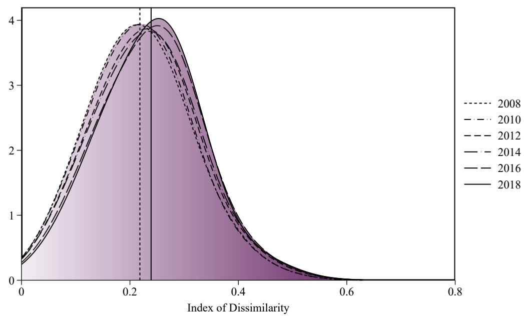
(e) Census Blocks, 2012 to 2020



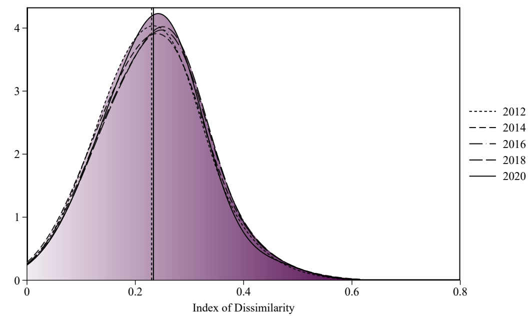
Notes: The figure plots kernel density estimates of the Democratic share at the county (Panel A), Congressional District (Panel B), Census Tract (Panel C), Census Block Group (Panel D), and Census Block (Panel E) levels. All panels use TargetSmart data for the 2012–2020 elections. All kernel density estimates are weighted by counts of registered voters in a given geographic unit-year and use a Gaussian kernel with bandwidth of 0.05.

Figure B.3 Distribution of the County- and Congressional District-Level Index of Dissimilarity, Catalist and TargetSmart Data

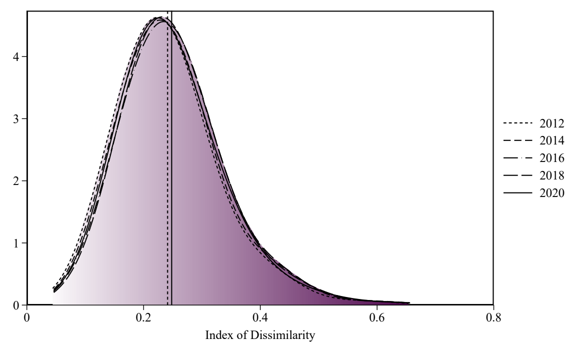
(a) Counties, 2008 to 2018, Catalist Data



(b) Counties, 2012 to 2020, TargetSmart Data

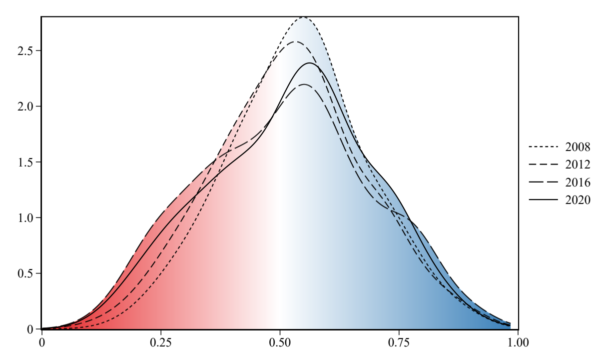


(c) Congressional Districts, 2012 to 2020, TargetSmart Data



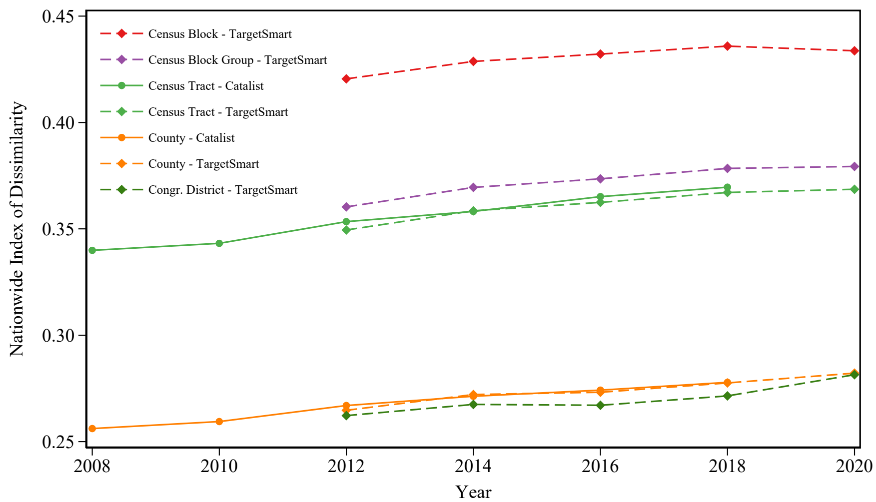
Notes: The figure plots kernel density estimates of the index of Dissimilarity at the county and Congressional District levels, using Census Tracts as subunits and weighting by counts of registered voters in a given geographic unit-year. Panel A is based on Catalist data, 2008–2018. Panels B and C are based on TargetSmart data, 2012–2020. Vertical lines represent year-specific (weighted) means for the first and last year. All kernel density estimates use a Gaussian kernel with bandwidth of 0.05.

Figure B.4 Distribution of the County-Level Two-Party Democratic Vote Share in Presidential Elections, Dave Leip's Atlas



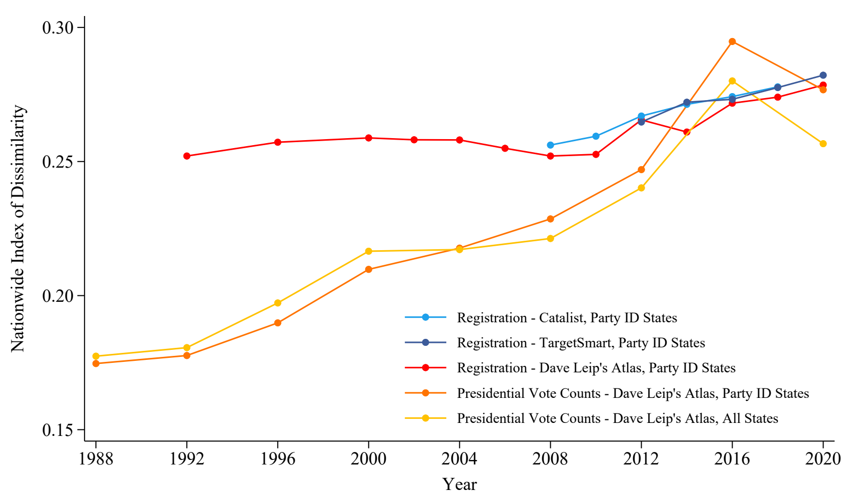
Notes: The figure plots kernel density estimates of the county-level two-party Democratic vote share in presidential elections, 2008–2020, using data from Dave Leip's Atlas of U.S. Presidential Elections. All kernel density estimates are weighted by counts of total ballots cast in a given county-year and use a Gaussian kernel with bandwidth of 0.05.

Figure B.5 Nationwide Index of Dissimilarity Across Geographic Subunits, Catalist and TargetSmart Data



Notes: The figure plots the over-time evolution of the nationwide index of Dissimilarity using data from Catalist and TargetSmart, for different types of geographic subunits. Different colors denote indices of Dissimilarity computed using different geographic subunits (e.g., red for Census Blocks and purple for Census Block Groups). Solid and dashed lines refer to indices of Dissimilarity computed using Catalist and TargetSmart data, respectively.

Figure B.6 Nationwide Index of Dissimilarity Across Data Sources



Notes: The figure plots the over-time evolution of the nationwide index of Dissimilarity using data from Catalist, TargetSmart, and Dave Leip's Atlas of U.S. Presidendial Elections. All series use counties as subunits. For both Catalist and TargetSmart, the plotted index of Dissimilarity is computed for the 29 states plus D.C. that record party affiliation. For Dave Leip's Atlas of U.S. Presidential Elections, we plot three series of the index of Dissimilarity: one for two-party voter registration shares in the 29 states plus D.C. that record party affiliation; one for two-party vote shares in presidential elections in all 50 states plus D.C.; and one for two-party vote shares in presidential elections in the 29 states plus D.C. that record party affiliation.

Table B.1 County- and Census Tract-Level Summary Statistics of the Share of Democrats among All Registrants, All Years, Catalist and TargetSmart Data

	Catalist		TargetSmart	
	Std. Dev.	Mean	Std. Dev.	Mean
	(1)	(2)	(3)	(4)
		Panel A. Counties		
2008	0.138	0.435	-	-
2010	0.139	0.428	-	-
2012	0.139	0.419	0.137	0.420
2014	0.139	0.412	0.140	0.415
2016	0.137	0.411	0.136	0.415
2018	0.134	0.404	0.135	0.406
2020	-	-	0.135	0.409
		Panel B. Census Tracts		
2008	0.171	0.437	-	-
2010	0.172	0.431	-	-
2012	0.173	0.421	0.170	0.420
2014	0.173	0.415	0.172	0.413
2016	0.171	0.413	0.170	0.413
2018	0.168	0.406	0.167	0.405
2020	-	-	0.165	0.408

Notes: The table reports county-level (Panel A) and Census Tract-level (Panel B) year-specific standard deviations and means of the share of Democrats among all registered voters, based on the Catalist and TargetSmart data. All statistics are weighted by counts of registered voters in each geographic unit in a given year.

Table B.2 County- and Census Tract-Level Summary Statistics of the Share of Republicans among All Registrants, All Years, Catalist and TargetSmart Data

	Catalist		TargetSmart	
	Std. Dev.	Mean	Std. Dev.	Mean
	(1)	(2)	(3)	(4)
		Panel A. Counties		
2008	0.122	0.305	-	-
2010	0.123	0.305	-	-
2012	0.125	0.300	0.125	0.303
2014	0.125	0.296	0.127	0.297
2016	0.128	0.296	0.129	0.299
2018	0.131	0.290	0.131	0.292
2020	-	-	0.136	0.295
		Panel B. Census Tracts		
2008	0.153	0.305	-	-
2010	0.154	0.304	-	-
2012	0.156	0.300	0.156	0.303
2014	0.156	0.296	0.157	0.298
2016	0.159	0.296	0.160	0.300
2018	0.160	0.290	0.161	0.293
2020	-	-	0.164	0.296

Notes: The table reports county-level (Panel A) and Census Tract-level (Panel B) year-specific standard deviations and means of the share of Republicans among all registered voters, based on the Catalist and TargetSmart data. All statistics are weighted by counts of registered voters in each geographic unit in a given year.

Table B.3 County- and Census Tract-Level Summary Statistics of the Democratic Share, All Years, Catalist and TargetSmart Data

	Catalist		TargetSmart	
	Std. Dev.	Mean	Std. Dev.	Mean
	(1)	(2)	(3)	(4)
		Panel A. Counties		
2008	0.155	0.587	-	-
2010	0.157	0.583	-	-
2012	0.161	0.582	0.159	0.581
2014	0.163	0.581	0.163	0.582
2016	0.165	0.581	0.164	0.582
2018	0.167	0.583	0.167	0.584
2020	-	-	0.170	0.584
		Panel B. Census Tracts		
2008	0.195	0.587	-	-
2010	0.197	0.584	-	-
2012	0.202	0.582	0.200	0.579
2014	0.204	0.581	0.204	0.580
2016	0.207	0.581	0.206	0.580
2018	0.209	0.583	0.208	0.581
2020	-	-	0.209	0.581

Notes: The table reports county-level (Panel A) and Census Tract-level (Panel B) year-specific standard deviations and means of the Democratic share, based on the Catalist and TargetSmart data. All statistics are weighted by counts of registered voters in each geographic unit in a given year.

Table B.4 Congressional District-, Census Block Group-, and Census Block-Level Summary Statistics of the Democratic Share, All Years, TargetSmart Data

	TargetSmart	
	Std. Dev.	Mean
	(1)	(2)
Panel A. Congressional Districts		
2012	0.156	0.581
2014	0.158	0.582
2016	0.158	0.582
2018	0.160	0.584
2020	0.164	0.584
Panel B. Census Block Groups		
2012	0.205	0.581
2014	0.210	0.581
2016	0.211	0.581
2018	0.213	0.583
2020	0.214	0.583
Panel C. Census Blocks		
2012	0.243	0.579
2014	0.245	0.582
2016	0.247	0.582
2018	0.248	0.584
2020	0.247	0.584

Notes: The table reports Congressional District- (Panel A), Census Block Group- (Panel B), and Census Block-level year-specific standard deviations and means of the Democratic share, based on the TargetSmart data. All statistics are weighted by counts of registered voters in each geographic unit in a given year.

Table B.5 County-Level Summary Statistics of the Index of Dissimilarity, All Years, Catalist and TargetSmart Data

	Catalist		TargetSmart	
	Std. Dev.	Mean	Std. Dev.	Mean
	(1)	(2)	(3)	(4)
2008	0.088	0.218	-	-
2010	0.088	0.220	-	-
2012	0.092	0.227	0.087	0.230
2014	0.092	0.230	0.091	0.233
2016	0.091	0.237	0.090	0.237
2018	0.089	0.239	0.089	0.238
2020	-	-	0.086	0.234

Notes: The table reports county-level year-specific standard deviations and means of the two-party index of Dissimilarity (using Census Tracts as subunits), based on the Catalist and TargetSmart data. All statistics are weighted by county-level counts of registered voters in a given year.

Table B.6 Congressional District-Level Summary Statistics of the Index of Dissimilarity, All Years, TargetSmart Data

	TargetSmart	
	Std. Dev.	Mean
	(1)	(2)
2012	0.081	0.241
2014	0.083	0.247
2016	0.083	0.252
2018	0.082	0.253
2020	0.082	0.248

Notes: The table reports Congressional District-level year-specific standard deviations and means of the two-party index of Dissimilarity (using Census Tracts as subunits), based on the TargetSmart data. All statistics are weighted by Congressional District-level counts of registered voters in a given year.

Table B.7 County-Level Statistics of the Two-Party Democratic Vote Share in Presidential Elections, All Years, Dave Leip's Atlas

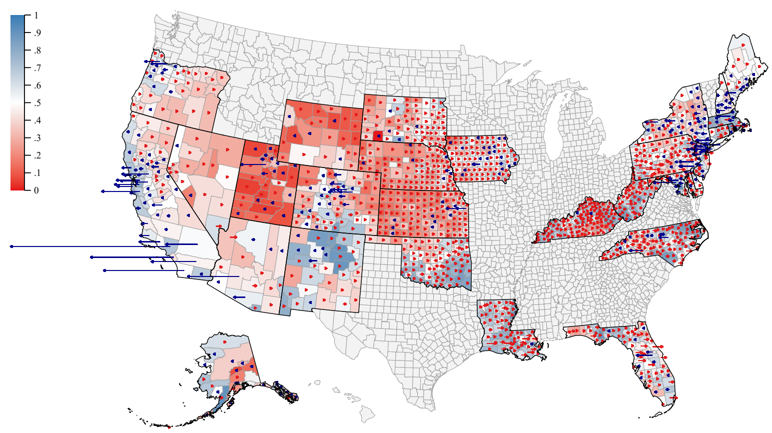
	Dave Leip's Atlas of U.S. Presidential Elections	
	Std. Dev.	Mean
	(1)	(2)
2008	0.144	0.537
2012	0.155	0.520
2016	0.179	0.511
2020	0.170	0.523

Notes: The table reports county-level year-specific standard deviations and means of the two-party Democratic vote share in presidential elections, based on Dave Leip's Atlas of U.S. Presidential Elections data. All statistics are weighted by county-level total votes cast in a given election.

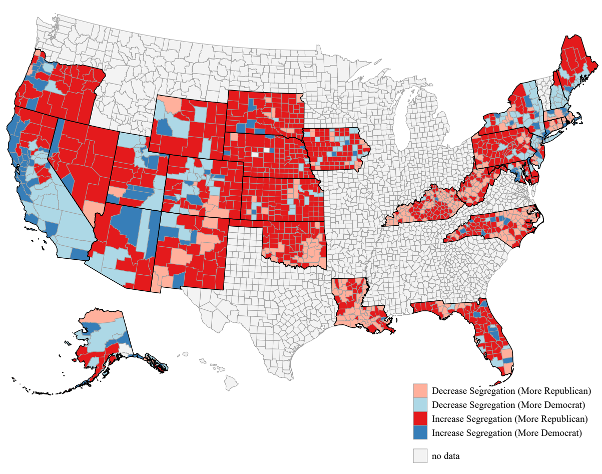
C. Areas Driving the Rise in Partisan Segregation, Additional Figures and Tables

Figure C.1 Change in the County-Level Democratic Share and in Partisan Segregation, 2012 to 2020, TargetSmart Data

(a) Change in the County-Level Democratic Share, 2012 to 2020

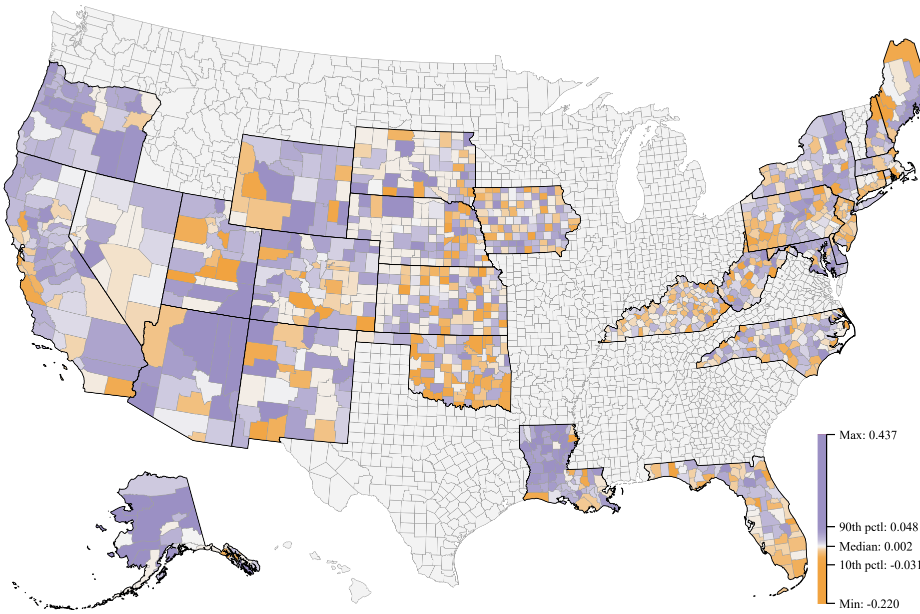


(b) Counties Contributing versus Resisting the Rise in Partisan Segregation, 2012 to 2020



Notes: In Panel A, for the 29 U.S. states (plus D.C.) that record party affiliation, counties are shaded red (more Republican) to blue (more Democratic) based on the Democratic share in 2012. Blue (resp. red) arrows mean that a county's Democratic share increased (resp. decreased) between 2012 and 2020. Arrow length is proportional to the magnitude of the change in the Democratic share, after weighting by baseline counts of registered voters in the county. Panel B shows counties that experienced an increase (colored in blue) versus a decrease (colored in red) of the Democratic share between 2012 and 2020. Light (resp. dark) shades of a color denote counties that contributed to reducing (resp. increasing) partisan segregation, by reducing (resp. increasing) the variance of the Democratic share. Both maps use 2012 and 2020 TargetSmart data.

Figure C.2 Change in the County-Level Index of Dissimilarity, 2012 to 2020, TargetSmart Data



Notes: For counties in the 29 states plus D.C. that record party affiliation, darker shades of purple (resp. orange) denote larger increases (resp. decreases) of the within-county index of Dissimilarity. The map is based on TargetSmart data, using Census Tracts as subunits.

Table C.1 Characteristics of Counties Contributing to the Rise in Partisan Segregation versus Resisting that Trend, TargetSmart Data

	Increase Segregation		Decrease Segregation	
	Democratic-Trending	Republican-Trending	Democratic-Trending	Republican-Trending
	(1)	(2)	(3)	(4)
	Panel A. Census Statistics			
Total population	452,414	49,070	321,808	100,409
Median age	37.11	41.43	37.14	39.78
Share female	0.511	0.505	0.509	0.512
HHI ethnic homogeneity	0.408	0.671	0.498	0.542
Share foreign-born	0.235	0.057	0.152	0.144
Share non-white	0.516	0.206	0.392	0.371
Population/Sq. mile	5,617	323	3,300	1,288
Share urban population	0.952	0.661	0.905	0.820
Median income	64,141	50,765	62,398	52,408
Gini index	0.480	0.442	0.461	0.468
High-school degree or above	0.861	0.877	0.876	0.863
Bachelor's degree or above	0.377	0.232	0.335	0.273
Share homeowners	0.574	0.719	0.641	0.661
	Panel B. Voter File Statistics on Registered Population			
Democrats	0.484	0.354	0.380	0.476
Independents	0.297	0.231	0.286	0.285
Republicans	0.219	0.415	0.334	0.239
Black	0.109	0.053	0.081	0.115
White	0.661	0.894	0.772	0.750
Hispanic	0.137	0.028	0.093	0.097
Number of counties	119	802	181	276

Notes: The table reports average demographic characteristics of counties that contributed to the increase in partisan segregation and of counties that decreased segregation, separately for counties that trended Democratic or Republican (i.e., counties that featured an increase versus a decrease in the Democratic share between 2012 and 2020). All figures are weighted by county-level counts of registered voters in 2012, except for total population figures that are unweighted. Census statistics in Panel A are based on 2015 5-year American Community Survey Data aggregated at the county level. Voter file statistics in Panel B are based on the 2012 TargetSmart data.

Table C.2 Characteristics of Census Tracts Contributing to the Rise in Partisan Segregation versus Resisting that Trend, TargetSmart Data

	Increase Segregation		Decrease Segregation	
	Democratic-Trending	Republican-Trending	Democratic-Trending	Republican-Trending
	(1)	(2)	(3)	(4)
Panel A. Census Statistics				
Total population	4,545	4,258	4,538	3,903
Median age	37.18	42.51	40.99	39.54
Share female	0.511	0.505	0.513	0.517
HHI ethnic homogeneity	0.515	0.732	0.630	0.622
Share foreign-born	0.226	0.067	0.131	0.133
Share non-white	0.508	0.189	0.321	0.408
Population/Sq. mile	11,782	1,755	6,264	6,750
Share urban population	0.964	0.618	0.912	0.857
Median income	68,605	56,710	77,377	49,072
Gini index	0.425	0.411	0.416	0.431
High-school degree or above	0.860	0.882	0.914	0.838
Bachelor's degree or above	0.379	0.236	0.399	0.225
Share homeowners	0.566	0.750	0.711	0.617
Panel B. Voter File Statistics on Registered Population				
Democrats	0.490	0.346	0.349	0.534
Independents	0.297	0.241	0.287	0.271
Republicans	0.213	0.413	0.364	0.194
Black	0.094	0.036	0.070	0.176
White	0.655	0.896	0.804	0.695
Hispanic	0.159	0.043	0.071	0.088
Number of Census Tracts	12,589	9,653	11,169	7,445

Notes: The table reports average demographic characteristics of Census Tracts that contributed to the increase in partisan segregation and of Census Tracts that decreased segregation, separately for tracts that trended Democratic or Republican (i.e., Census Tracts that featured an increase versus a decrease in the Democratic share between 2012 and 2020). All figures are weighted by Census Tract-level counts of registered voters in 2012, except for total population figures that are unweighted. Census statistics in Panel A are based on 2015 5-year American Community Survey Data aggregated at the Census Tract level. Voter file statistics in Panel B are based on the 2012 TargetSmart data.

Table C.3 Changes in Characteristics of Counties Contributing to the Rise in Partisan Segregation versus Resisting that Trend, Catalist Data

	Increase Segregation		Decrease Segregation	
	Democratic-Trending	Republican-Trending	Democratic-Trending	Republican-Trending
	(1)	(2)	(3)	(4)
Panel A. Census Statistics				
Δ Total population	117,667	39,431	122,219	23,106
Δ Median age	1.61	2.14	2.03	1.69
Δ Share female	0.001	0.0005	0.002	-0.00004
Δ HHI ethnic homogeneity	-0.041	-0.075	-0.060	-0.074
Δ Share foreign-born	0.008	0.006	0.003	0.012
Δ Share non-white	0.054	0.059	0.062	0.061
Δ Population/Sq. mile	567	40	83	69
Δ Share urban population	-0.004	-0.018	-0.010	-0.024
Δ Median income	29,572	19,578	26,932	18,696
Δ Gini index	0.009	0.012	0.010	0.013
Δ High-school degree or above	0.030	0.034	0.029	0.036
Δ Bachelor's degree or above	0.064	0.051	0.060	0.051
Δ Share homeowners	-0.005	0.009	0.004	-0.004
Panel B. Voter File Statistics on Registered Population				
Δ Democrats	-0.011	-0.063	0.001	-0.055
Δ Independents	0.050	0.045	0.045	0.031
Δ Republicans	-0.039	0.018	-0.046	0.024
Δ Black	0.005	0.005	0.005	0.012
Δ White	-0.063	-0.031	-0.057	-0.038
Δ Hispanic	0.035	0.019	0.036	0.016
Number of counties	91	762	115	405

Notes: The table reports 2020-minus-2010 differences in demographic characteristics of counties that contributed to the increase in partisan segregation and of counties that decreased segregation, separately for counties that trended Democratic or Republican (i.e., counties that featured an increase versus a decrease in the Democratic share between 2008 and 2018). All figures are weighted by county-level counts of registered voters in 2008, except for total population figures that are unweighted. Census statistics in Panel A are based on the 2010 decennial census, the 2012 5-year American Community Survey, the 2020 decennial census, and the 2022 5-year American Community Survey, all aggregated at the county level. Voter file statistics in Panel B are based on the 2008 and 2018 Catalist data.

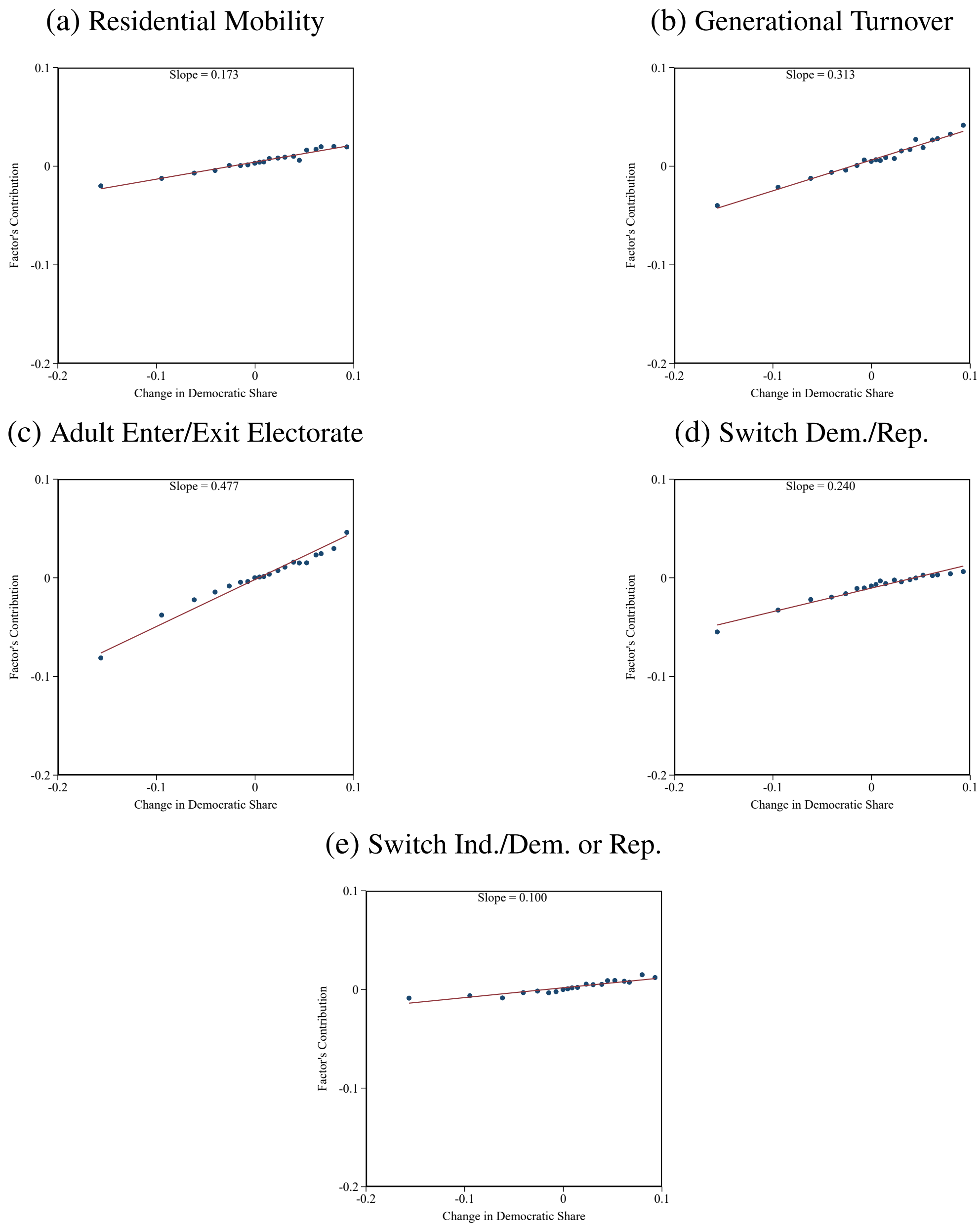
Table C.4 Changes in Characteristics of Counties Contributing to the Rise in Partisan Segregation versus Resisting that Trend, TargetSmart Data

	Increase Segregation		Decrease Segregation	
	Democratic-Trending	Republican-Trending	Democratic-Trending	Republican-Trending
	(1)	(2)	(3)	(4)
Panel A. Census Statistics				
Δ Total population	109,167	20,704	112,888	58,936
Δ Median age	1.71	2.08	1.86	1.77
Δ Share female	0.001	0.0001	0.001	0.0005
Δ HHI ethnic homogeneity	-0.045	-0.077	-0.062	-0.064
Δ Share foreign-born	0.008	0.005	0.005	0.014
Δ Share non-white	0.059	0.056	0.060	0.061
Δ Population/Sq. mile	401	28	259	87
Δ Share urban population	-0.004	-0.022	-0.009	-0.016
Δ Median income	29,484	19,327	26,325	18,938
Δ Gini index	0.009	0.012	0.010	0.013
Δ High-school degree or above	0.028	0.036	0.029	0.037
Δ Bachelor's degree or above	0.061	0.050	0.062	0.053
Δ Share homeowners	-0.003	0.010	0.003	-0.007
Panel B. Voter File Statistics on Registered Population				
Δ Democrats	0.014	-0.058	0.021	-0.046
Δ Independents	0.022	0.025	0.012	0.023
Δ Republicans	-0.036	0.034	-0.033	0.024
Δ Black	-0.001	0.001	-0.001	0.001
Δ White	-0.048	-0.021	-0.039	-0.031
Δ Hispanic	0.028	0.012	0.023	0.018
Number of counties	119	802	181	276

Notes: The table reports 2020-minus-2010 differences in demographic characteristics of counties that contributed to the increase in partisan segregation and of counties that decreased segregation, separately for counties that trended Democratic or Republican (i.e., counties that featured an increase versus a decrease in the Democratic share between 2012 and 2020). All figures are weighted by county-level counts of registered voters in 2008, except for total population figures that are unweighted. Census statistics in Panel A are based on the 2010 decennial census, the 2012 5-year American Community Survey, the 2020 decennial census, and the 2022 5-year American Community Survey, all aggregated at the county level. Voter file statistics in Panel B are based on the 2012 and 2020 TargetSmart data.

D. Factors Driving the Increase in Partisan Segregation, Additional Figures and Tables

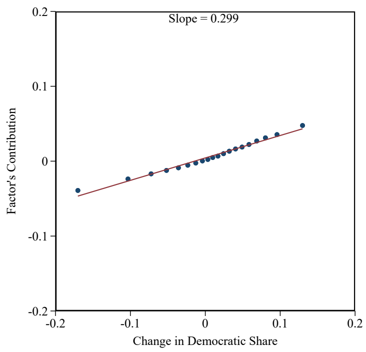
Figure D.1 Factors Contributing to the County-Level Change in the Democratic Share, 2012 to 2020, TargetSmart Data



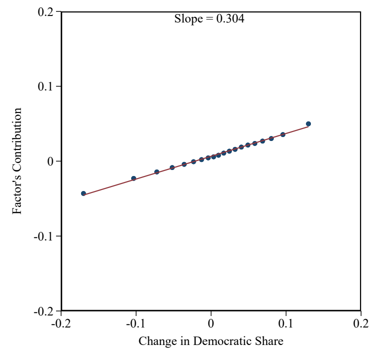
Notes: Using 2012 and 2020 TargetSmart data, each binscatter plot displays the county-level relationship between the over-time change in the Democratic share (x-axis) and a decomposition factor's contribution (y-axis). The red line represents the best linear fit, estimated weighting counties by 2012 counts of registered voters.

Figure D.2 Factors Contributing to the Census Tract-Level Change in the Democratic Share, 2012 to 2020, TargetSmart Data

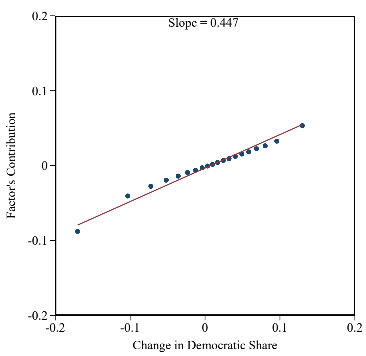
(a) Residential Mobility



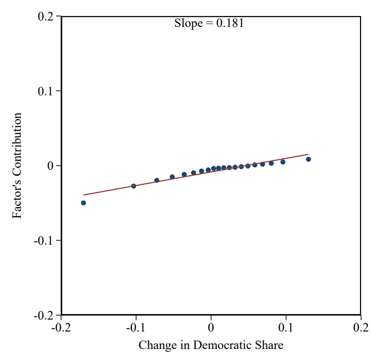
(b) Generational Turnover



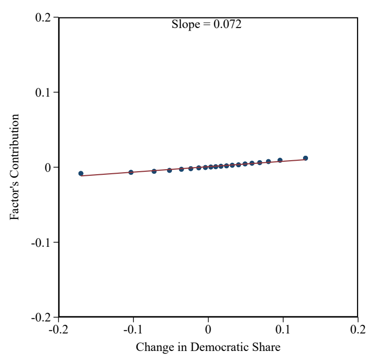
(c) Adult Enter/Exit Electorate



(d) Switch Dem./Rep.

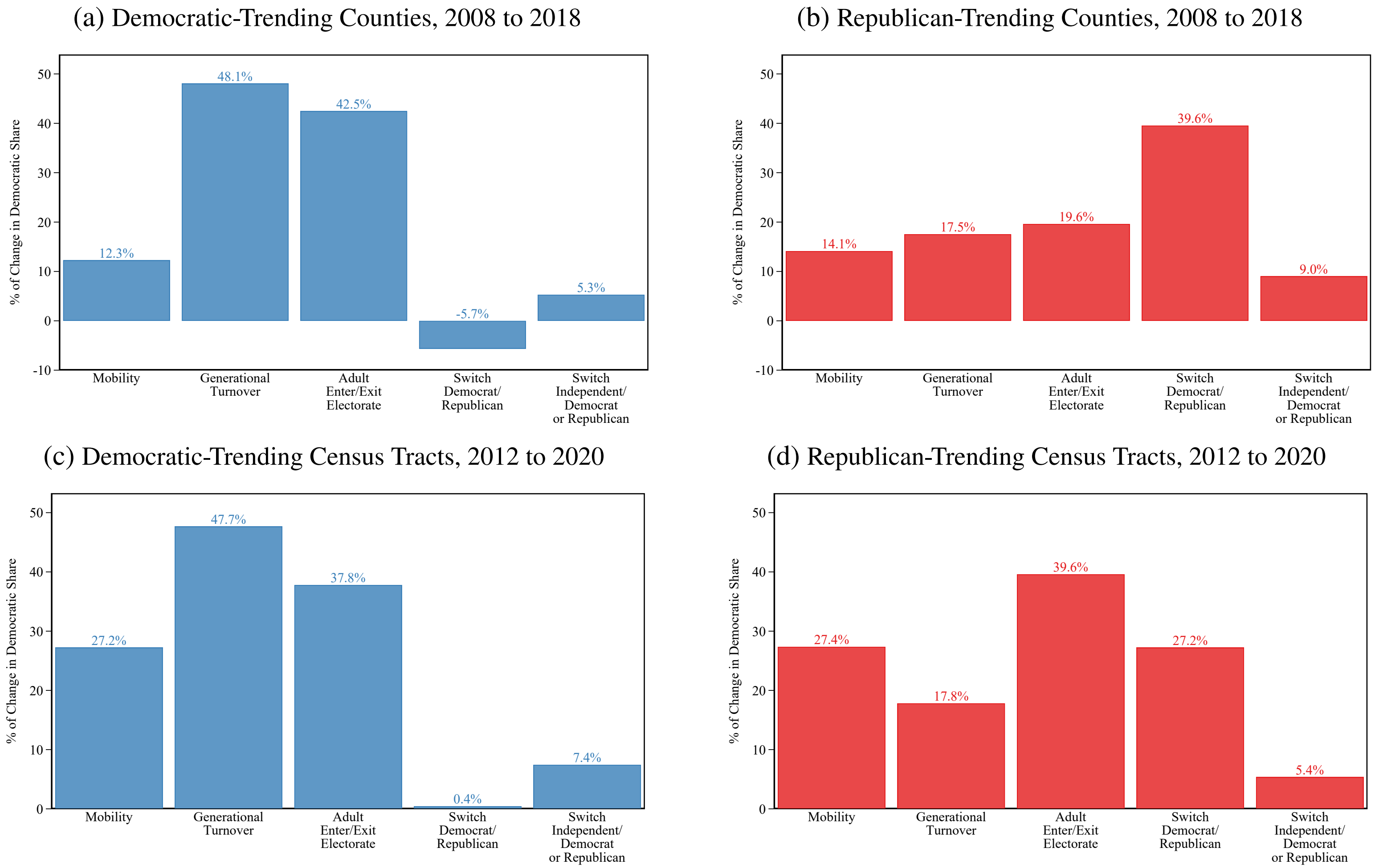


(e) Switch Ind./Dem. or Rep.



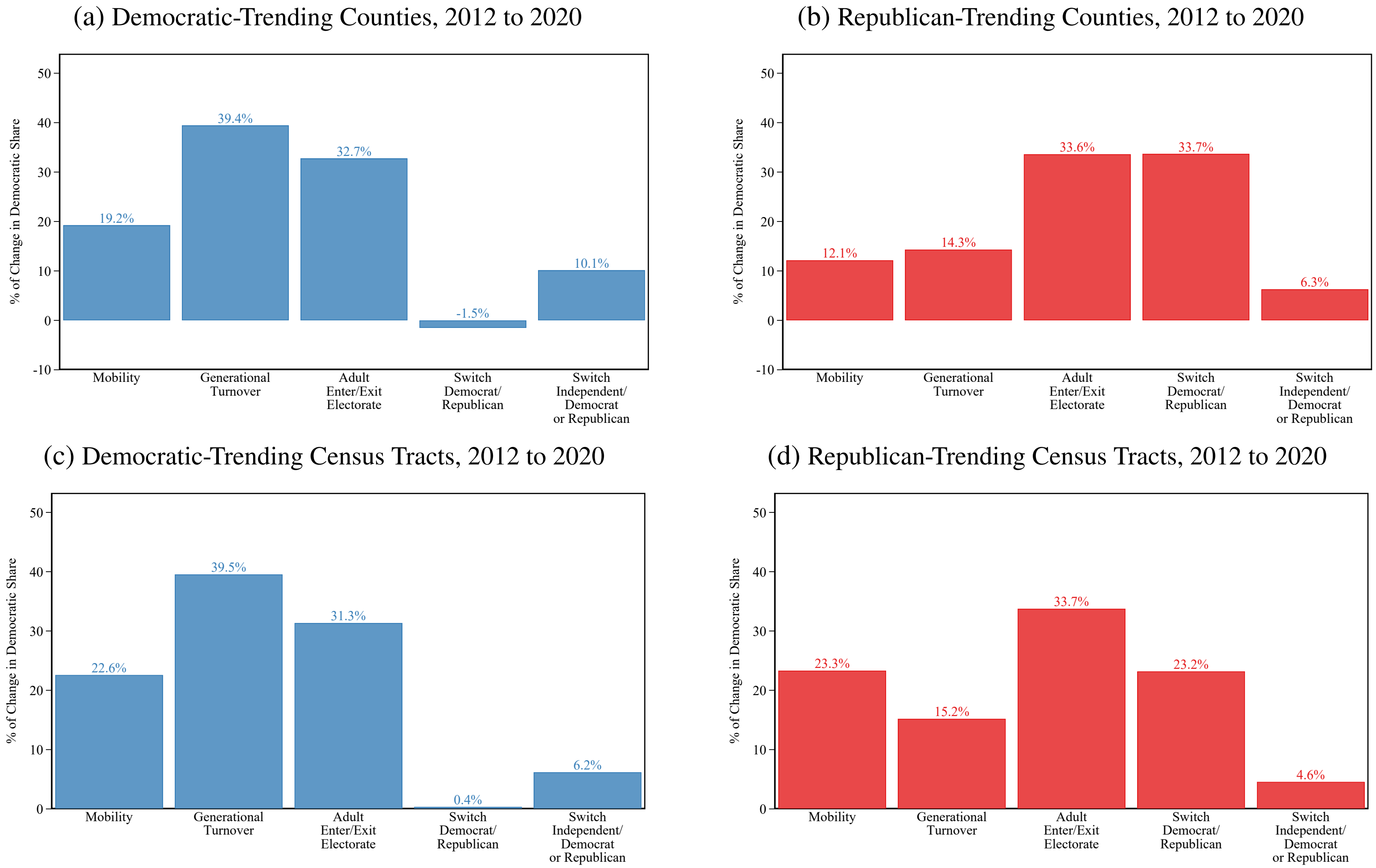
Notes: Using 2012 and 2020 TargetSmart data, each binscatter plot displays the Census Tract-level relationship between the over-time change in the Democratic share (x-axis) and a decomposition factor's contribution (y-axis). The red line represents the best linear fit, estimated weighting Census Tracts by 2012 counts of registered voters.

Figure D.3 Factors Driving Changes in the Democratic Share: Normalizing Factor Importance by $\Delta_g \frac{D}{D+R}$ Instead of $\sum f' \lambda_{g,f'}$



Notes: Each plot shows the percentage of the change in the Democratic share explained by different decomposition factors. Panels A and B are based on 2008 and 2018 Catalist county-level data; Panels C and D are based on 2012 and 2020 TargetSmart Census Tract-level data. Samples for Panels A and C (resp. B and D) consist of Democratic-leaning (resp. Republican-leaning) geographic units; that is, geographic units that witnessed an increase (resp. a decrease) in the Democratic share over the period. Factor shares plotted in this figure come from dividing decomposition factors by $\Delta_g \frac{D}{D+R}$ instead of $\sum f' \lambda_{g,f'}$, as done in Figure VI.

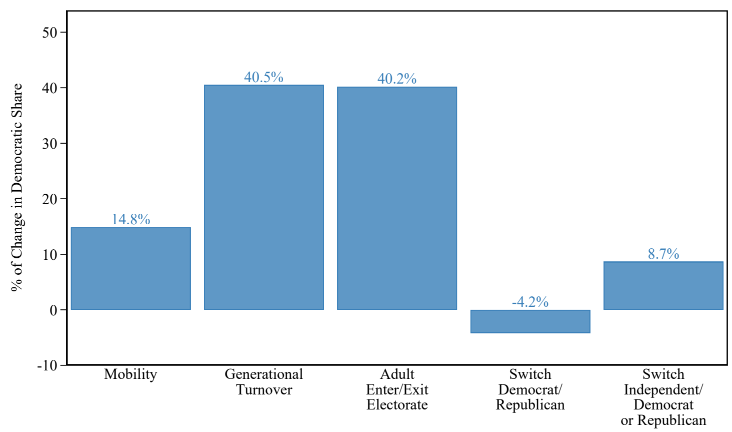
Figure D.4 Factors Driving Changes in the Democratic Share, 2012 to 2020, TargetSmart Data



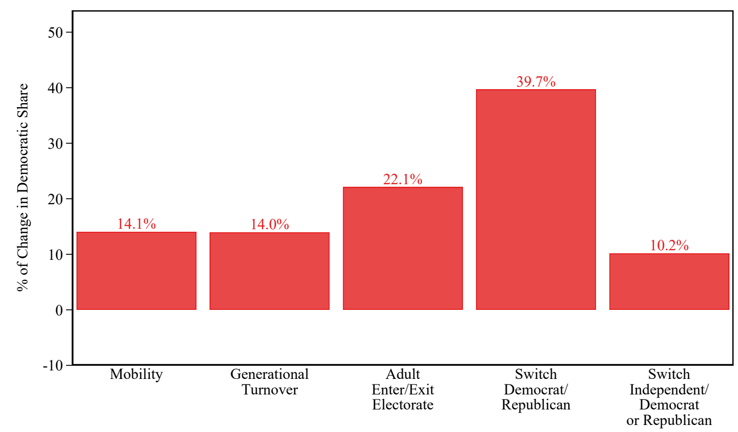
Notes: Each plot shows the percentage of the change in the Democratic share explained by different decomposition factors using 2012 and 2020 TargetSmart data. Panels A and B are based on county-level data; Panels C and D are based on Census Tract-level data. Samples for Panels A and C (resp. B and D) consist of Democratic-leaning (resp. Republican-leaning) geographic units; that is, geographic units that witnessed an increase (resp. a decrease) in the Democratic share over the period.

Figure D.5 Factors Driving Changes in the County-Level Democratic Share by Segregation Trends, 2008 to 2018, Catalist Data

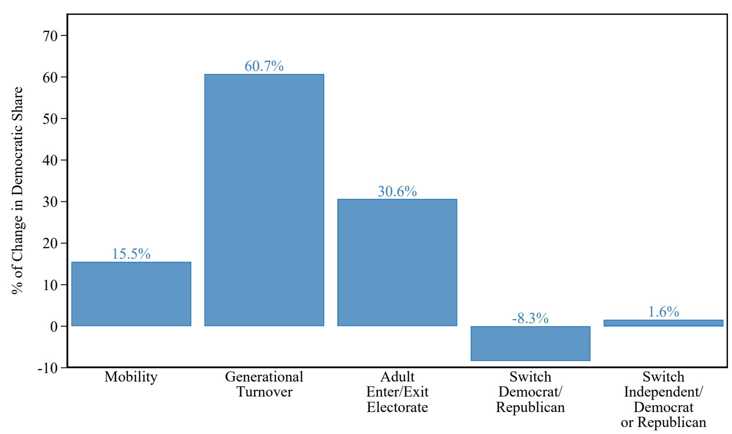
(a) Democratic-Trending Counties, Increasing Segregation



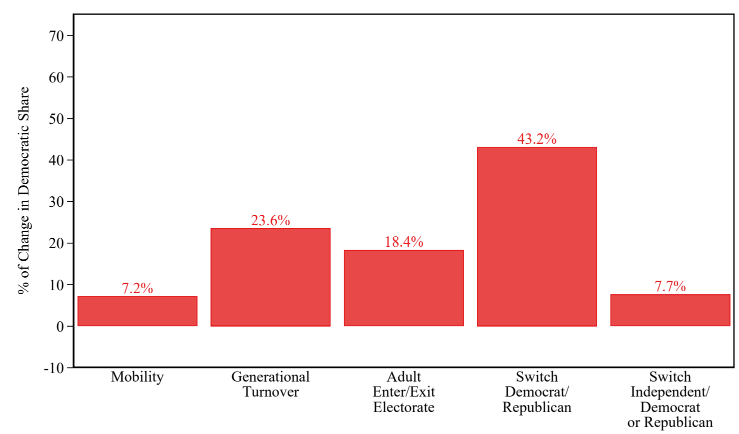
(b) Republican-Trending Counties, Increasing Segregation



(c) Democratic-Trending Counties, Decreasing Segregation

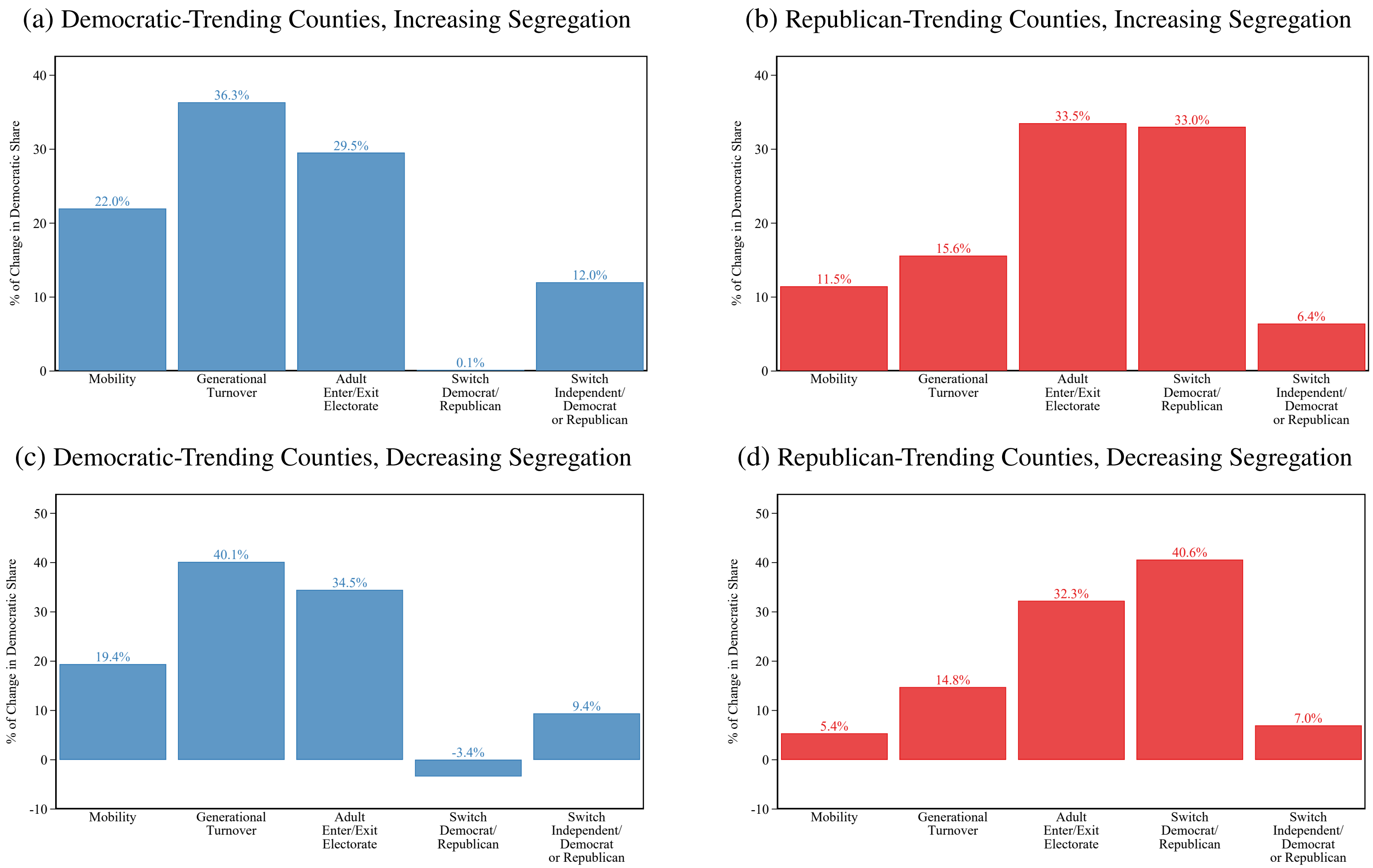


(d) Republican-Trending Counties, Decreasing Segregation



Notes: Each plot shows the percentage of the 2008-to-2018 change in the Democratic share explained by different decomposition factors. All panels are based on Catalist data. Each panel represents a different group of counties. Specifically, we split counties into four groups based on whether, between 2008 and 2018, they saw an increase versus a decrease in the Democratic share (Panels A and C versus Panels B and D) and on whether they contributed to increasing versus decreasing the variance of the Democratic share (Panels A and B versus Panels C and D).

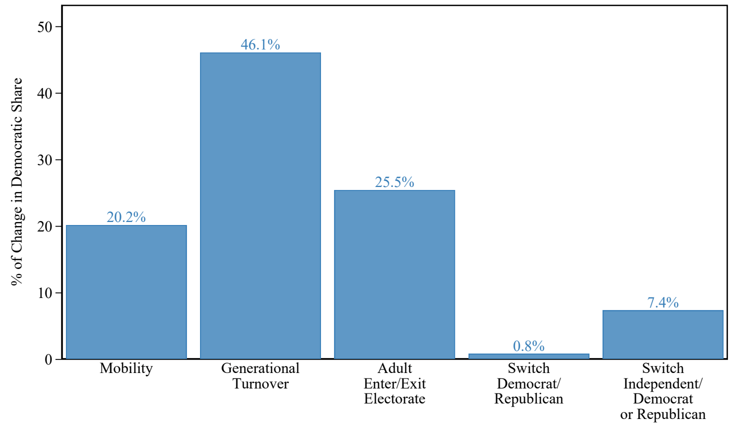
Figure D.6 Factors Driving Changes in the County-Level Democratic Share by Segregation Trends, 2012 to 2020, TargetSmart Data



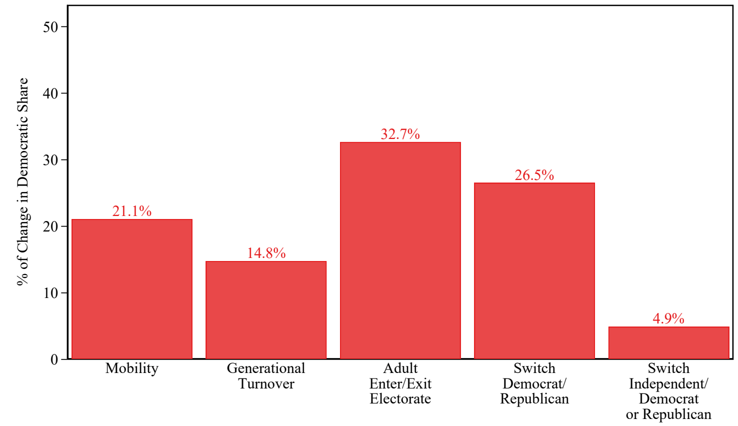
Notes: Each plot shows the percentage of the 2012-to-2020 change in the Democratic share explained by different decomposition factors. All panels are based on TargetSmart data. Each panel represents a different group of counties. Specifically, we split counties into four groups based on whether, between 2012 and 2020, they saw an increase versus a decrease in the Democratic share (Panels A and C versus Panels B and D) and on whether they contributed to increasing versus decreasing the variance of the Democratic share (Panels A and B versus Panels C and D).

Figure D.7 Factors Driving Changes in the Census Tract-Level Democratic Share by Segregation Trends, 2012 to 2020, TargetSmart Data

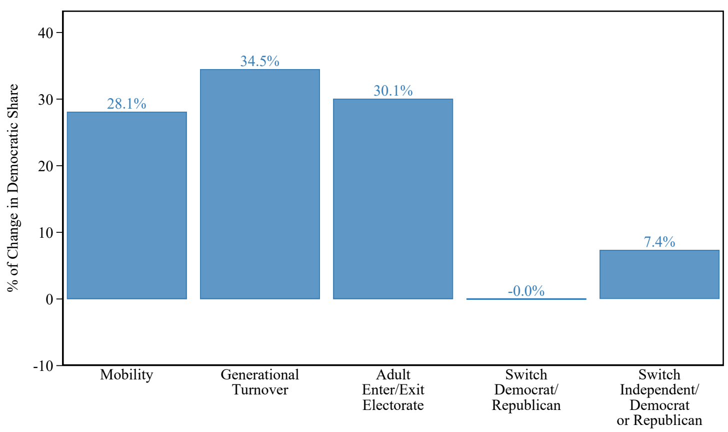
(a) Democratic-Trending Census Tracts, Increasing Segregation



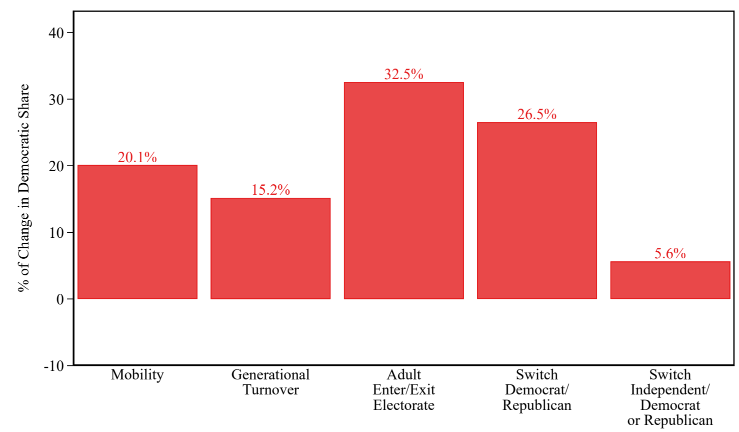
(b) Republican-Trending Census Tracts, Increasing Segregation



(c) Democratic-Trending Census Tracts, Decreasing Segregation



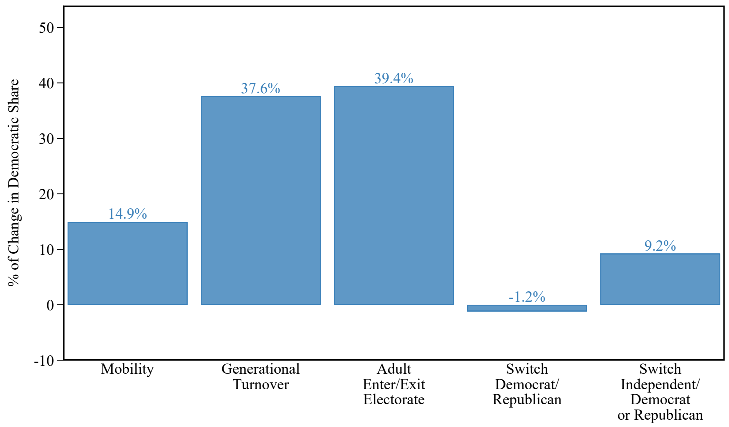
(d) Republican-Trending Census Tracts, Decreasing Segregation



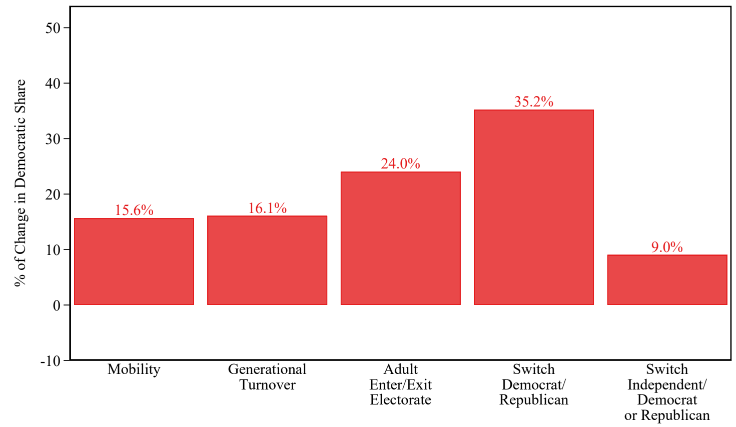
Notes: Each plot shows the percentage of the 2012-to-2020 change in the Democratic share explained by different decomposition factors. All panels are based on TargetSmart data. Each panel represents a different group of Census Tracts. Specifically, we split Census Tracts into four groups based on whether, between 2012 and 2020, they saw an increase versus a decrease in the Democratic share (Panels A and C versus Panels B and D) and on whether they contributed to increasing versus decreasing the variance of the Democratic share (Panels A and B versus Panels C and D).

Figure D.8 Factors Driving Changes in the Democratic Share by Extreme County Segregation Trends, 2008 to 2018, Catalist Data

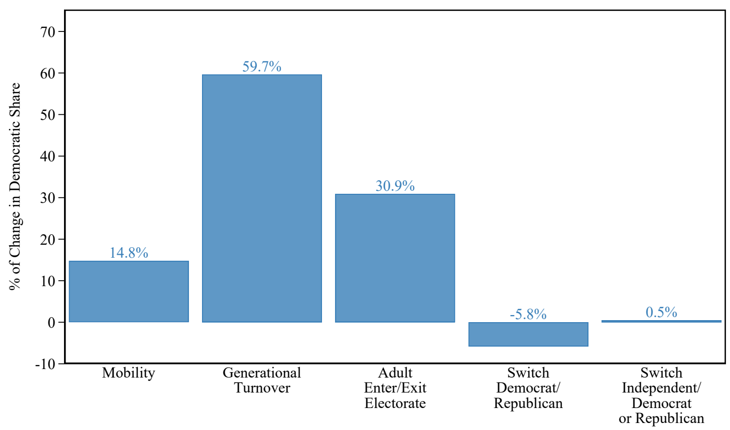
(a) Democratic-Trending Counties, Increasing Segregation



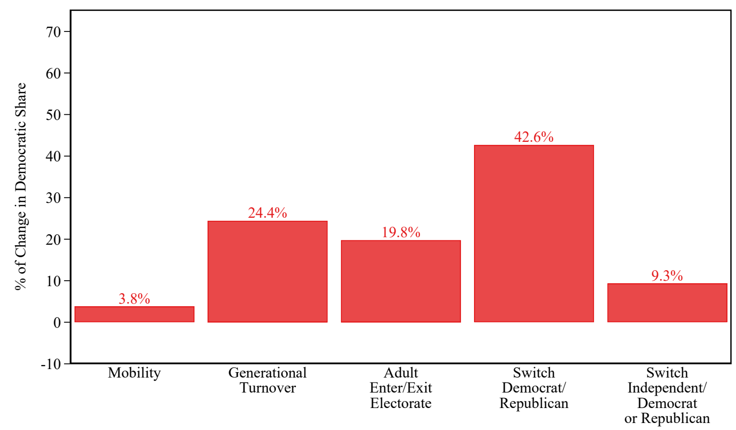
(b) Republican-Trending Counties, Increasing Segregation



(c) Democratic-Trending Counties, Decreasing Segregation



(d) Republican-Trending Counties, Decreasing Segregation



Notes: Each plot shows the percentage of the 2008-to-2018 change in the Democratic share explained by different decomposition factors. All panels are based on Catalist data. Each panel represents a different group of counties. Specifically, we split counties into four groups based on whether, between 2008 and 2018, they saw an extreme increase versus an extreme decrease in the Democratic share (Panels A and C versus Panels B and D) and on whether they were among the 10% of counties that most contributed to increasing versus the 10% of counties that most contributed to decreasing the variance of the Democratic share (Panels A and B versus Panels C and D).

Table D.1 Counts of Movers, New Registrants, Party Switchers, and Voters who Died or Became Unregistered

	Movers	New Young Voters	New Adult Voters	Party Switchers	Deregisters	Died	Voters First Year	Voters Last Year
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A. Catalist, 2008-2018				
County	12,476,146	16,142,133	15,645,143	8,340,674	18,339,436	9,074,711	99,239,654	107,182,121
Census Tract	36,901,599	14,952,379	14,623,162	3,477,152	17,009,463	7,932,314	93,129,048	101,101,906
				Panel B. TargetSmart, 2012-2020				
County	12,298,434	14,772,749	16,514,858	8,244,382	4,829,440	14,460,118	84,797,031	103,676,124
Census Tract	24,927,289	14,758,119	16,358,633	5,182,393	4,766,272	14,280,979	84,140,083	103,275,810

Notes: The table reports counts of county- and Census-Tract-specific categories of voters defined using the first and last years of the Catalist (Panel A) and TargetSmart data (Panel B). Movers (column 1) are defined as voters who are registered in different geographies at baseline and endline. New young voters (column 2) are registered voters who are 25 or younger at endline. New adult voters (column 3) are voters who are unregistered at baseline but who, at endline, are older than 25 and are registered. Party switchers (column 4) are registered voters who are affiliated with a different major party at baseline and endline. Deregisters (column 5) are voters who were registered at baseline and who appear in the data as not being registered at endline. Dead voters (column 6) are voters registered at baseline but not in the data (whether as registered or unregistered) at endline. Columns 7 and 8 report total counts of voters in the first and last years for a given data source and geographic sample.

Table D.2 Factors Driving Changes in the County- and Census Tract-Level Democratic Share by Year Pairs, Catalist and TargetSmart Data

	Democratic-Trending Counties/Census Tracts					Republican-Trending Counties/Census Tracts				
	Mobility	Gen. Turnover	Adult Enter/ Exit Electorate	Switch Dem./ Rep.	Switch Ind./ Dem. or Rep.	Mobility	Gen. Turnover	Adult Enter/ Exit Electorate	Switch Dem./ Rep.	Switch Ind./ Dem. or Rep.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					Panel A. Catalist, Counties					
2008-2012	13.6	37.2	48.7	-10.1	10.6	9.6	21.7	12.6	40.0	16.0
2012-2018	16.0	36.1	39.2	-2.6	11.3	12.9	13.1	23.5	41.5	9.0
					Panel B. TargetSmart, Counties					
2012-2016	15.0	36.8	42.6	-3.9	9.5	9.1	16.2	30.6	37.7	6.4
2016-2020	22.0	30.2	27.0	3.0	17.8	13.3	9.6	27.2	42.4	7.6
					Panel C. TargetSmart, Census Tracts					
2012-2016	21.5	36.6	39.1	-2.5	5.4	22.5	16.3	29.9	26.0	5.4
2016-2020	29.6	29.7	22.6	4.8	13.3	26.3	11.1	24.1	31.7	7.0

Notes: The table reports the percentage of the change in the Democratic share explained by each decomposition factor across pairs of years, using the Catalist county-level (Panel A) and TargetSmart county- (Panel B) and Census Tract-level data (Panel C). For each pair of years and data source, we classify geographic units as Democratic-trending versus Republican-trending depending on whether, between those two election years, counties or Census Tracts featured an increase versus a decrease in the Democratic share.

Table D.3 County-Level Factors' Scale and Partisan Tilt, 2012 to 2020, TargetSmart Data

	Democratic-Trending Counties				Republican-Trending Counties			
	$N^{I}_{g,f}$	$N^{o}_{g,f}$	$s^{I}_{g,f}$ - $D_{y1}/(D_{y1} + R_{y1})$	$s^{O}_{g,f}$ - $D_{y1}/(D_{y1} + R_{y1})$	$N^{I}_{g,f}$	$N^{o}_{g,f}$	$s^{I}_{g,f}$ - $D_{y1}/(D_{y1} + R_{y1})$	$s^{O}_{g,f}$ - $D_{y1}/(D_{y1} + R_{y1})$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mobility	5,018,811	5,266,056	0.058	-0.007	3,470,916	3,072,132	-0.095	-0.039
Gen. Turnover	5,853,603	6,050,753	0.126	0.011	3,145,064	4,406,206	-0.032	0.034
Adult Enter/Exit Electorate	9,011,800	2,118,997	0.053	-0.036	6,337,479	1,509,978	-0.088	0.016
Switch Dem./Rep.	1,229,249		-0.010		1,063,738		-0.286	
Switch Ind./Dem. or Rep.	2,481,746	1,593,811	0.037	-0.051	1,127,325	748,513	-0.058	0.058
Baseline Registrants Counts	52,256,415				32,540,616			

Notes: The table is based on the TargetSmart data. For each decomposition factor (in rows), the table disaggregates the factor's contribution to the 2012-to-2020 county-level change in the Democratic share between the factor's scale (columns 1-2 and 5-6) and partisan tilt (columns 3-4 and 7-8). Columns 1-4 refer to counties that became more Democratic between 2012 and 2020, while columns 5-8 refer to counties that became more Republican over the same period.

Table D.4 Census Tract-Level Factors' Scale and Partisan Tilt, 2012 to 2020, TargetSmart Data

	Democratic-Trending Census Tracts				Republican-Trending Census Tracts			
	$N^{I}_{g,f}$	$N^{o}_{g,f}$	$s^{I}_{g,f}$ - $D_{y1}/(D_{y1} + R_{y1})$	$s^{O}_{g,f}$ - $D_{y1}/(D_{y1} + R_{y1})$	$N^{I}_{g,f}$	$N^{o}_{g,f}$	$s^{I}_{g,f}$ - $D_{y1}/(D_{y1} + R_{y1})$	$s^{O}_{g,f}$ - $D_{y1}/(D_{y1} + R_{y1})$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mobility	11,008,608	10,809,542	0.053	0.012	6,730,724	6,287,346	-0.082	-0.010
Gen. Turnover	5,724,105	5,778,452	0.141	0.003	3,250,608	4,551,914	-0.047	0.037
Adult Enter/Exit Electorate	8,634,381	2,018,900	0.063	-0.041	6,497,102	1,570,758	-0.105	0.019
Switch Dem./Rep.	788,623		0.004		808,013		-0.324	
Switch Ind./Dem. or Rep.	1,455,268	866,581	0.045	-0.068	777,611	486,296	-0.092	0.051
Baseline Registrants Counts	50,476,963				33,662,753			

Notes: The table is based on the TargetSmart data. For each decomposition factor (in rows), the table disaggregates the factor's contribution to the 2012-to-2020 Census Tract-level change in the Democratic share between the factor's scale (columns 1-2 and 5-6) and partisan tilt (columns 3-4 and 7-8). Columns 1-4 refer to Census Tracts that became more Democratic between 2012 and 2020, while columns 5-8 refer to Census Tracts that became more Republican over the same period.

Table D.5 County-Level Factor's Scale and Partisan Tilt by Segregation Trends, 2008 to 2018, Catalist Data

	Democratic-Trending Counties				Republican-Trending Counties			
	$N^I_{g,f}$	$N^o_{g,f}$	$s^I_{g,f}$ - $D_{y1}/(D_{y1} + R_{y1})$	$s^O_{g,f}$ - $D_{y1}/(D_{y1} + R_{y1})$	$N^I_{g,f}$	$N^o_{g,f}$	$s^I_{g,f}$ - $D_{y1}/(D_{y1} + R_{y1})$	$s^O_{g,f}$ - $D_{y1}/(D_{y1} + R_{y1})$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A. Increasing Segregation				
Mobility	2,348,713	2,844,820	0.035	-0.014	3,091,644	2,614,223	-0.085	-0.038
Gen. Turnover	3,171,315	2,097,906	0.101	-0.005	2,417,026	2,127,013	-0.020	0.054
Adult Enter/Exit Electorate	4,006,573	3,807,304	0.081	-0.001	3,148,526	3,782,918	-0.041	0.034
Switch Dem./Rep.	498,018		-0.029		828,720		-0.274	
Switch Ind./Dem. or Rep.	1,011,546	974,575	0.011	-0.061	803,621	656,107	-0.101	0.058
Baseline Registrants Counts	30,949,486				27,514,386			
				Panel B. Decreasing Segregation				
Mobility	1,787,951	1,858,179	0.049	0.006	1,363,325	1,510,595	-0.103	-0.063
Gen. Turnover	2,162,676	1,467,020	0.138	-0.004	1,746,055	1,677,128	-0.048	0.039
Adult Enter/Exit Electorate	2,451,993	3,052,959	0.087	0.019	1,856,899	2,203,159	-0.052	0.009
Switch Dem./Rep.	490,098		-0.043		526,085		-0.282	
Switch Ind./Dem. or Rep.	792,090	702,502	-0.004	-0.016	573,605	483,707	-0.091	-0.007
Baseline Registrants Counts	21,895,617				18,880,165			

Notes: The table is based on the Catalist data. For each decomposition factor (in rows), the table disaggregates the factor's contribution to the 2008-to-2018 county-level change in the Democratic share between the factor's scale (columns 1-2 and 5-6) and partisan tilt (columns 3-4 and 7-8). Panels A and B refer to, respectively, counties that contributed to increasing versus decreasing the variance of the Democratic share. Moreover, columns 1-4 refer to counties that became more Democratic between 2008 and 2018, while columns 5-8 refer to counties that became more Republican over the same period.

Table D.6 County-Level Factor's Scale and Partisan Tilt, 2008 to 2012 and 2012 to 2018, Catalist Data

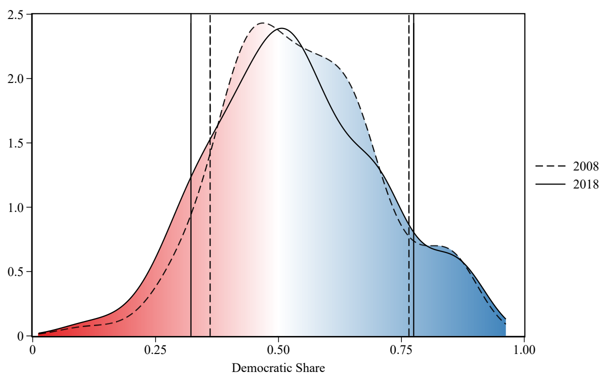
	Democratic-Trending Counties				Republican-Trending Counties			
	$N^I_{g,f}$	$N^o_{g,f}$	$s^I_{g,f}$ - $D_{y1}/(D_{y1} + R_{y1})$	$s^O_{g,f}$ - $D_{y1}/(D_{y1} + R_{y1})$	$N^I_{g,f}$	$N^o_{g,f}$	$s^I_{g,f}$ - $D_{y1}/(D_{y1} + R_{y1})$	$s^O_{g,f}$ - $D_{y1}/(D_{y1} + R_{y1})$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A. 2008 to 2012				
Mobility	1,932,060	2,164,161	0.039	0.009	2,667,921	2,665,989	-0.065	-0.036
Gen. Turnover	1,954,691	1,603,066	0.071	-0.011	2,041,571	1,916,695	-0.031	0.059
Adult Enter/Exit Electorate	2,474,605	3,077,902	0.080	-0.001	2,429,128	3,492,189	-0.011	0.022
Switch Dem./Rep.	436,901		-0.045		671,359		-0.250	
Switch Ind./Dem. or Rep.	691,890	710,288	0.021	-0.042	901,714	809,639	-0.122	0.024
Baseline Registrants Counts	45,952,146				53,287,508			
				Panel B. 2012 to 2018				
Mobility	3,889,289	4,234,349	0.040	-0.004	3,217,530	2,943,520	-0.095	-0.052
Gen. Turnover	3,568,231	1,747,629	0.112	0.004	2,254,426	1,716,525	-0.025	0.058
Adult Enter/Exit Electorate	5,290,458	5,532,484	0.082	0.001	3,265,027	3,858,363	-0.049	0.031
Switch Dem./Rep.	877,397		-0.015		935,683		-0.273	
Switch Ind./Dem. or Rep.	2,084,956	1,654,929	0.031	-0.036	1,151,554	813,880	-0.053	0.057
Baseline Registrants Counts	58,790,607				41,597,071			

Notes: The table is based on the Catalist data. For each decomposition factor (in rows), the table disaggregates the factor's contribution to the 2008-to-2012 (Panel A) or to the 2012-to-2018 (Panel B) county-level change in the Democratic share between the factor's scale (columns 1-2 and 5-6) and partisan tilt (columns 3-4 and 7-8). Columns 1-4 refer to counties that became more Democratic over each panel's sample period, while columns 5-8 refer to counties that became more Republican over the same period.

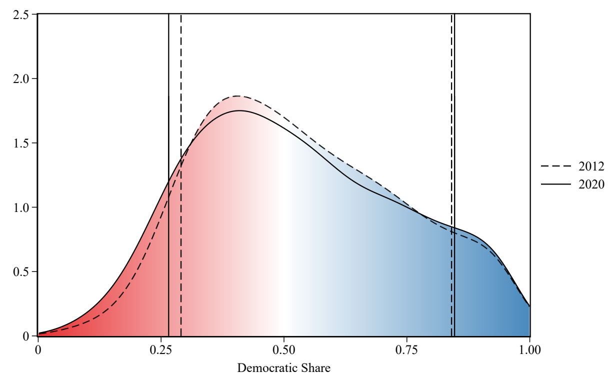
E. Changes in Partisan Segregation and Demographic Groups, Additional Figures and Tables

Figure E.1 Distribution of the Democratic Share by Gender

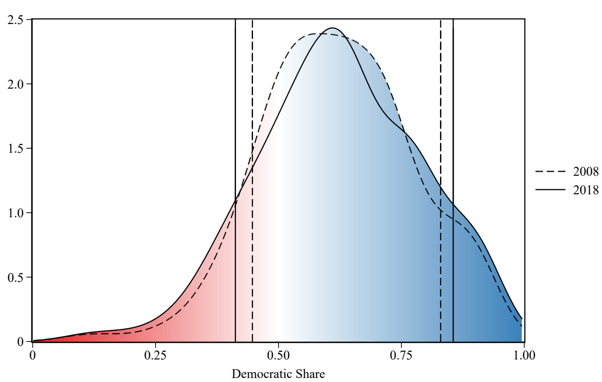
(a) Male, Counties, 2008 and 2018



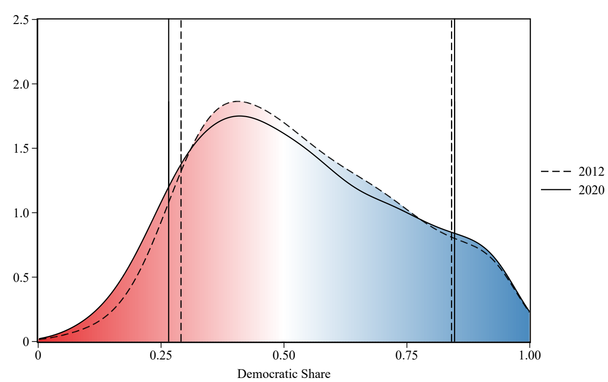
(b) Male, Census Tracts, 2012 and 2020



(c) Female, Counties, 2008 and 2018



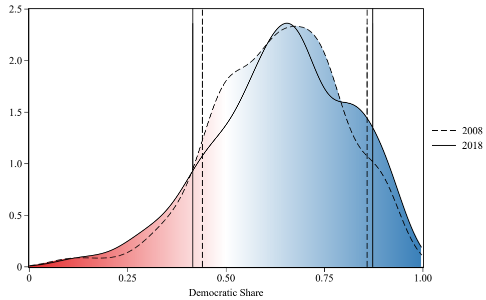
(d) Female, Census Tracts, 2012 and 2020



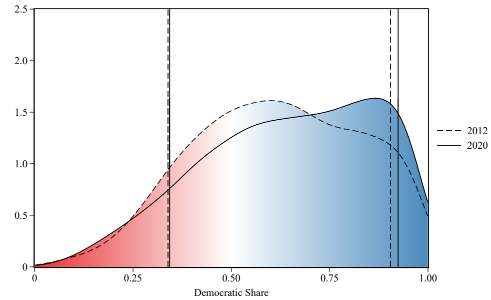
Notes: We show kernel density plots of the gender-specific Democratic share. All kernel density estimates are weighted by gender-specific counts of registered voters in a given geographic unit-year and use a Gaussian kernel with bandwidth of 0.05. In each plot, vertical lines represent the 10th (vertical lines on the left tail of each plot) and 90th percentiles (vertical lines on the right tail of each plot). Panels A and C use the county-level Catalist data for the 2008 and 2018 elections. Panels B and D use the Census Tract-level TargetSmart data for the 2012 and 2020 elections.

Figure E.2 Distribution of the Democratic Share by Age Quartile

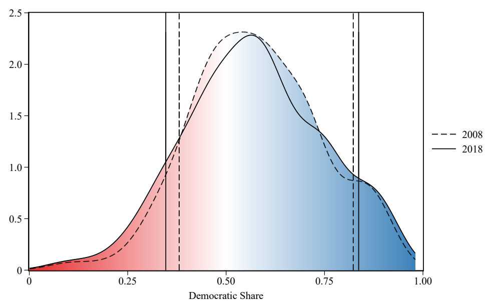
(a) Age Q1, Counties, 2008 and 2018



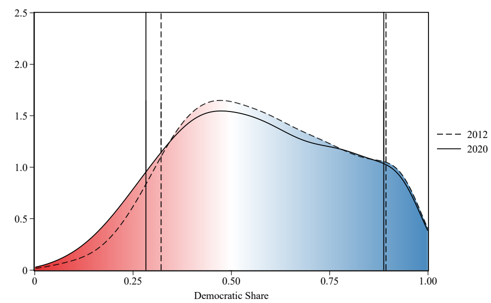
(b) Age Q1, Census Tracts, 2012 and 2020



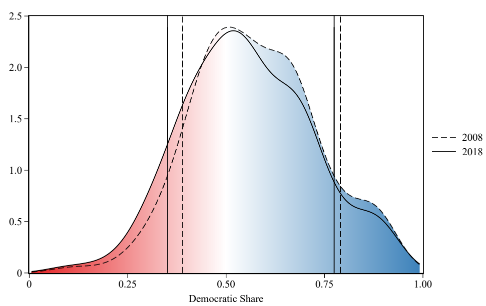
(c) Age Q2, Counties, 2008 and 2018



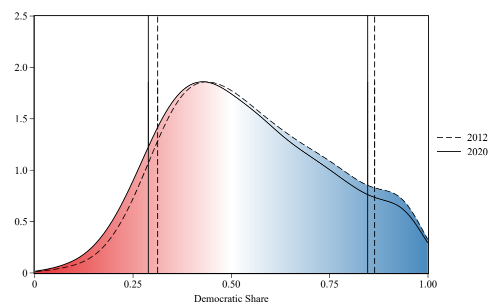
(d) Age Q2, Census Tracts, 2012 and 202



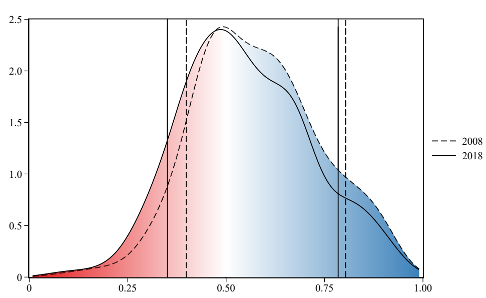
(e) Age Q3, Counties, 2008 and 2018



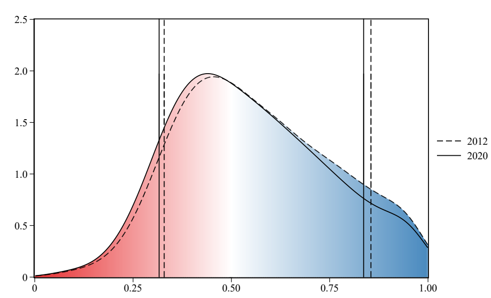
(f) Age Q3, Census Tracts, 2012 and 2020



(g) Age Q4, Counties, 2008 and 2018



(h) Age Q4, Census Tracts, 2012 and 2020



Notes: We show kernel density plots of the age quartile-specific Democratic share. All kernel density estimates are weighted by age quartile-specific counts of registered voters in a given geographic unit-year and use a Gaussian kernel with bandwidth of 0.05. In each plot, vertical lines represent the 10th (vertical lines on the left tail of each plot) and 90th percentiles (vertical lines on the right tail of each plot). Panels A, C, E, and G use the county-level Catalist data for the 2008 and 2018 elections. Panels B, D, F, and H use the Census Tract-level TargetSmart data for the 2012 and 2020 elections.

Table E.1 County- and Census Tract-Level Summary Statistics of the Democratic Share by Age, Baseline and Endline Years, Catalist and TargetSmart Data

		Catalist		TargetSmart	
		Std. Dev.	Mean	Std. Dev.	Mean
		(1)	(2)	(3)	(4)
		Panel A. Counties			
Aged 18-27 (Q1)	Baseline	0.160	0.633	0.164	0.620
	Endline	0.173	0.642	0.176	0.651
Aged 28-42 (Q2)	Baseline	0.162	0.577	0.168	0.590
	Endline	0.176	0.574	0.181	0.576
Aged 43-57 (Q3)	Baseline	0.157	0.575	0.161	0.562
	Endline	0.164	0.556	0.166	0.543
Aged 58+ (Q4)	Baseline	0.157	0.579	0.160	0.569
	Endline	0.162	0.549	0.161	0.553
		Panel B. Census Tracts			
Aged 18-27 (Q1)	Baseline	0.200	0.633	0.209	0.618
	Endline	0.215	0.641	0.217	0.649
Aged 28-42 (Q2)	Baseline	0.206	0.577	0.211	0.588
	Endline	0.220	0.573	0.222	0.573
Aged 43-57 (Q3)	Baseline	0.198	0.575	0.203	0.560
	Endline	0.206	0.555	0.207	0.540
Aged 58+ (Q4)	Baseline	0.195	0.578	0.196	0.567
	Endline	0.199	0.549	0.196	0.550

Notes: The table reports county-level (Panel A) and Census Tract-level (Panel B) age-specific standard deviations and means of Democratic share, based on the Catalist (columns 1-2) and TargetSmart data (columns 3-4). "Baseline" refers to 2008 and 2012 for the Catalist and TargetSmart data, respectively. "Endline" refers to 2018 and 2020 for the Catalist and TargetSmart data, respectively. All statistics are weighted by counts of registered voters of the corresponding age quartile in each geographic unit in a given year.

Table E.2 County- and Census Tract-Level Summary Statistics of the Democratic Share by Gender, Baseline and Endline Years, Catalist and TargetSmart Data

		Catalist		TargetSmart	
		Std. Dev.	Mean	Std. Dev.	Mean
		(1)	(2)	(3)	(4)
		Panel A. Counties			
Male	Baseline	0.157	0.545	0.161	0.538
	Endline	0.170	0.533	0.173	0.531
Female	Baseline	0.153	0.620	0.157	0.615
	Endline	0.165	0.623	0.167	0.624
		Panel B. Census Tracts			
Male	Baseline	0.199	0.546	0.204	0.537
	Endline	0.214	0.534	0.214	0.529
Female	Baseline	0.191	0.620	0.196	0.614
	Endline	0.204	0.622	0.205	0.621

Notes: The table reports county-level (Panel A) and Census Tract-level (Panel B) gender-specific standard deviations and means of Democratic share, based on the Catalist (columns 1-2) and TargetSmart data (columns 3-4). "Baseline" refers to 2008 and 2012 for the Catalist and TargetSmart data, respectively. "Endline" refers to 2018 and 2020 for the Catalist and TargetSmart data, respectively. All statistics are weighted by counts of registered voters of the corresponding gender in each geographic unit in a given year.

Table E.3 County- and Census Tract-Level Summary Statistics of the Democratic Share by Race, Baseline and Endline Years, Catalist and TargetSmart Data

		Catalist		TargetSmart	
		Std. Dev.	Mean	Std. Dev.	Mean
		(1)	(2)	(3)	(4)
		Panel A. Counties			
Black	Baseline	0.054	0.934	0.041	0.948
	Endline	0.050	0.941	0.039	0.951
Hispanic	Baseline	0.134	0.747	0.132	0.759
	Endline	0.114	0.781	0.121	0.777
White	Baseline	0.146	0.515	0.151	0.507
	Endline	0.158	0.482	0.166	0.494
Other race	Baseline	0.122	0.680	0.126	0.675
	Endline	0.114	0.726	0.117	0.717
		Panel B. Census Tracts			
Black	Baseline	0.071	0.935	0.059	0.947
	Endline	0.066	0.941	0.054	0.950
Hispanic	Baseline	0.158	0.747	0.157	0.759
	Endline	0.143	0.782	0.144	0.777
White	Baseline	0.174	0.515	0.179	0.508
	Endline	0.184	0.482	0.193	0.493
Other race	Baseline	0.155	0.677	0.159	0.674
	Endline	0.146	0.722	0.145	0.715

Notes: The table reports county-level (Panel A) and Census Tract-level (Panel B) race-specific standard deviations and means of Democratic share, based on the Catalist (columns 1-2) and TargetSmart data (columns 3-4). "Baseline" refers to 2008 and 2012 for the Catalist and TargetSmart data, respectively. "Endline" refers to 2018 and 2020 for the Catalist and TargetSmart data, respectively. All statistics are weighted by counts of registered voters of the corresponding race in each geographic unit in a given year.

Table E.4 Demographic Groups' Contribution to Factors Driving County-Level Changes in the Democratic Share, 2012 to 2020, TargetSmart Data

	Democratic-Trending Counties						Republican-Trending Counties					
		Factors						Factors				
	% Voters	Mobility	Gen. Turnover	Adult Enter/ Exit Electorate	Switch Dem./ Rep.	Switch Ind./ Dem. or Rep.	% Voters	Mobility	Gen. Turnover	Adult Enter/ Exit Electorate	Switch Dem./ Rep.	Switch Ind./ Dem. or Rep.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Panel A. Overall Contribution						Panel A. Overall Contribution					
		19.2	39.4	32.7	-1.5	10.1		12.1	14.3	33.6	33.7	6.3
	Panel B. By Age Quartile						Panel B. By Age Quartile					
Aged 18-27 (Q1)	20.6	12.0	40.9	10.8	2.4	5.2	17.8	0.8	7.0	3.9	2.5	0.3
Aged 28-42 (Q2)	25.4	2.2	-3.4	12.3	-1.4	2.4	23.5	3.6	1.5	11.5	8.5	2.3
Aged 43-57 (Q3)	26.1	3.3	-0.9	2.5	-0.9	1.8	26.5	4.8	1.5	11.0	11.7	2.1
Aged 58+ (Q4)	28.0	1.8	3.3	5.7	-1.6	0.8	32.2	3.0	4.4	6.5	11.0	1.6
	Panel C. By Sex						Panel C. By Sex					
Male	46.3	9.6	9.9	5.2	-2.0	3.2	46.5	7.2	10.2	21.9	16.1	3.8
Female	53.7	9.6	25.1	24.9	0.5	6.8	53.5	4.9	4.0	11.6	17.5	2.5
	Panel D. By Race						Panel D. By Race					
Black	9.4	-0.7	-2.4	13.9	0.5	0.9	7.9	-0.2	2.2	-8.2	-0.03	-0.3
Hispanic	11.4	-0.1	12.8	17.2	-0.04	1.8	5.7	0.1	-1.8	-3.4	0.8	-0.1
White	71.9	18.9	21.3	-6.5	-2.1	6.0	83.4	12.1	15.0	46.2	32.4	6.8
Other race	7.2	1.0	7.8	8.1	0.1	1.4	3.0	0.1	-1.1	-1.1	0.4	-0.1

Notes: The table is based on the TargetSmart data. Panel A reports the share of the change in the Democratic share attributable to each decomposition factor, separately for counties that became more Democratic (columns 1-6) or more Republican (columns 7-12) between 2012 and 2020. Each cell in Panels B, C, and D shows how much a given demographic group (in rows) contributed to a given factor's share of the decomposition (in columns). Vertical sums within panels add up to a given factor's overall contribution reported in Panel A, up to an error term due to voters with missing age or gender information (voters with missing race are instead included in the "Other race" category). For example, generational turnover explains 39.4% of the change in the Democratic share in counties that became more Democratic; -2.4, 12.8, 21.3, and 7.8 percentage points of this 39.4% are due to, respectively, Black, Hispanic, White, and other-race voters (i.e., -2.4% + 12.8% + 21.3% + 7.8% = 39.4%). Columns 1 and 7 report the fractions of voters belonging to each demographic group in 2012.

Table E.5 Demographic Groups' Contribution to Factors Driving Changes in the Census Tract-Level Democratic Share, 2012 to 2020, TargetSmart Data

	Democratic-Trending Census Tracts						Republican-Trending Census Tracts					
		Factors						Factors				
	% Voters	Mobility	Gen. Turnover	Adult Enter/ Exit Electorate	Switch Dem./ Rep.	Switch Ind./ Dem. or Rep.	% Voters	Mobility	Gen. Turnover	Adult Enter/ Exit Electorate	Switch Dem./ Rep.	Switch Ind./ Dem. or Rep.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Panel A. Overall Contribution						Panel A. Overall Contribution					
		22.6	39.5	31.3	0.4	6.2		23.3	15.2	33.7	23.2	4.6
	Panel B. By Age Quartile						Panel B. By Age Quartile					
Aged 18-27 (Q1)	20.5	14.7	38.2	10.1	1.2	2.2	18.1	3.3	8.2	4.1	1.1	0.1
Aged 28-42 (Q2)	25.2	2.9	-2.7	12.3	-0.3	1.6	23.6	7.6	1.3	11.5	5.2	1.5
Aged 43-57 (Q3)	26.2	3.2	-0.5	3.0	0.14	1.6	26.5	7.5	1.3	10.5	8.6	1.7
Aged 58+ (Q4)	28.2	1.8	4.5	5.9	-0.7	0.8	31.8	4.9	4.5	7.0	8.4	1.4
	Panel C. By Sex						Panel C. By Sex					
Male	46.3	10.0	11.1	6.2	-0.5	2.1	46.4	12.5	10.1	20.9	11.0	2.6
Female	53.7	12.6	24.2	22.9	0.8	4.0	53.6	10.8	4.9	12.6	12.2	1.9
	Panel D. By Race						Panel D. By Race					
Black	8.2	0.7	0.2	10.7	0.3	0.5	9.5	0.8	3.0	-7.0	-0.01	-0.33
Hispanic	11.3	1.0	11.3	14.7	0.1	0.9	6.2	0.9	-1.5	-3.3	0.5	-0.2
White	73.3	19.4	21.2	-1.0	-0.15	3.9	81.1	21.2	14.4	44.9	22.5	5.1
Other race	7.3	1.4	6.9	7.0	0.1	0.9	3.2	0.4	-0.7	-0.8	0.3	-0.05

Notes: The table is based on the TargetSmart data. Panel A reports the share of the change in the Democratic share attributable to each decomposition factor, separately for Census Tracts that became more Democratic (columns 1-6) or more Republican (columns 7-12) between 2012 and 2020. Each cell in Panels B, C, and D shows how much a given demographic group (in rows) contributed to a given factor's share of the decomposition (in columns). Vertical sums within panels add up to a given factor's overall contribution reported in Panel A, up to an error term due to voters with missing age or gender information (voters with missing race are instead included in the "Other race" category). For example, generational turnover explains 39.5% of the change in the Democratic share in Census Tracts that became more Democratic; 0.2, 11.3, 21.2, and 6.9 percentage points of this 39.5% are due to, respectively, Black, Hispanic, White, and other-race voters (i.e., 0.2% + 11.3% + 21.2% + 6.9% = 39.5%). Columns 1 and 7 report the fractions of voters belonging to each demographic group in 2012.

Appendix References

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