Online Appendix

Intersections of Class and Race

American cities are segregated by race and socioeconomic class (Fry and Taylor 2012; Oliver 1999). The scale of segregation grew from blocks in the 19th century to neighborhood to municipality (Trounstine 2018). Ultimately, segregation is a network of local government policy decisions. Historically, local governments used zoning ordinances and city plans to segregate cities by both race and class, to the benefit of businesses and wealthier neighborhoods and in defense of high property values (Trounstine 2018). The legacies of segregation are proliferated through modern suburbs and enclaves within cities. Consequences of segregation on socioeconomic status and various differences in public health, crime, and mobility out of low-income neighborhoods are extensive (Iton and Ross 2017; Sharkey 2013). District reforms may have larger representation impacts in cities with higher levels of segregation, since minority representation has been found to be lowest in cities with both at-large systems *and* higher segregation (Vedlitz and Johnson 1982). Class segregation can result in increased consolidation of political opinions shared by neighbors with similar socioeconomic status, contributing to polarized voting by neighborhood and overrepresentation of wealthier neighborhoods in city politics (Jargowsky 1996; Baldassarri and Bearman 2007; Ballí 2013).

District reforms are not intended as mechanisms to redistribute wealth or diversify neighborhoods themselves, but to increase representation for underrepresented neighborhoods, often lower income and less educated electorates relative to the city as a whole (Harjunen, Saarimaa, and Tukiainen 2023). A mechanical result of district reforms is expanding the geographic center of power. An ancillary result from district reforms is increasing diversity in the source and backing of political power of who gets elected. For instance, Banfield and Wilson (1963) note that districts inherently affect the balance of local power by including a variety of interests from smaller-scale economies that thrive in lower-income, immigrant, and communities of color outside traditional downtown centers of commerce. Eulau and Prewitt (1973) find more electoral competition in "poorer" communities, where candidates are fostered by civic organizations like trade unions and ethnic associations that cater to the interests of a more diverse community.

While organizations like chambers of commerce are often supportive of at-large councils (Stone 2019; Bridges 1997), small business owners may be empowered to seek office in a district election. In smaller scale economies within lower-income neighborhoods and communities of color, persistent and intertwined with continuing legacies of housing segregation, business owners are often prominent community leaders alongside religious leaders and educators. For instance, Latino business owners are the fastest growing entrepreneurs in the US, yet are more likely to have lower socioeconomic status than their white counterparts (Cimini 2020). Small businesses are connectors and pillars of racial and ethnic minorities' neighborhoods, "far more important as 'community institutions' rather than simply as factors in a market nexus" (Ingham 1993). Jacobs (1961) refers to small businesses as "the eyes and ears" of the street, keeping watch over the community. The importance of businesses to neighborhoods like these positions owners as leaders, and logical candidates for local office.

Additional Detail on Data Construction

Matching Block Groups to Districts. For block groups split across multiple districts, we observe the share of block group population contained within each district the block group overlaps. (We are able to observe population counts within these intersections, because we have aggregated these mappings up from individual-level voter registration files.) We can then identify the district the block group is primarily contained within, as measured by population share. Call this the “primary match". Amongst primary matches, the median of population share contained within a district is 100%. The 25th percentile is 99.8%. In 86% of cases, at least 95% of the block group is contained within the primary match district. Thus, the most typical case of splitting is one where the vast majority (e.g., more than 95%) is contained within one district and a very small population count is outside of that primary match.

There is a very small number (roughly 100 or <1% of the total) of block groups for which no district contains more than 50% of its population; we therefore cannot match these and they are dropped from the dataset.

An alternative approach might be to, for example, drop split block groups. As noted 29% of block groups are split, so that would lead to substantial lost data. We adopt our approach in light of the minimal magnitude of the splitting that does happen – by “minimal magnitude” we refer to the fact that even those block groups that are split are still almost entirely contained within a single district. We might adopt a different approach if instead block groups were more frequently evenly split across two districts.

Identifying Candidate Demographics

For candidate race and gender, we draw on data from Beach and Jones (2017) and Beach et al. (forthcoming). The process draws on three distinct sources. The first is hand-collecting photographs of candidates, then uploading the photos to Amazon’s Mechanical Turk (mTurk) to code candidates’ likely race and gender. Multiple mTurk workers (3-10) code each photo and candidates with substantial disagreement between mTurk workers are excluded from the database. The second source is interest group databases, namely the *National Association of Latino Elected Officials (NALEO)* and *Asian Pacific American Insitute for Congressional Studies (APAICS)*. Both list elected officials nationwide at a variety of levels of government from their respective racial/ethnic groups. The methods outlined above identify race/ethnicity and gender only for a subset of candidates. Race/ethnicity is identified for roughly 58% of the candidates in the sample.

Alternate Means of Coding Candidates Based on Occupation. We adopted an alternate means of coding candidates based on their occupation. Specifically, we used a large-language model to identify "high earning" occupations and "working class" occupations, based on the ballot designation provided. We then processed the data in the same way as described above, identifying whether a candidate is ever identified as one of these two categories. We present some appendix results using these alternative classifications. There are some advantages to this approach: because our main coding method is manual, it is difficult to systematically identify all relevant keywords, especially those occurring infrequently. This approach overcomes that problem; it does so, though, potentially at the expense of categorizing some terms as "higher earning" that should not be. Thus, we view each approach as having benefits and drawbacks. Note that this alternative classification captures a slightly different concept than our manual coding, identifying "high earners" more generally and not specifically those in "business"/"profit-oriented" professions.

Description of Additional Robustness Tests

We present a series of figures repeating our main analysis with variations to probe the robustness of our results. We restrict to city-year observations where we have identified the relevant outcome for all winning candidates (Appendix Figure A3); we add time-varying controls (Appendix Figure A4); and we expand our sample to include "always districted cities" into the control group (Appendix Figure A7). All results are similar to our main results.

Next, one might worry that localities that shifted to district-based elections during our sample period are dramatically different than those that did not. This of course would only bias results if this difference materializes in distinct trends – as the fixed effects already account for differences in levels. Nonetheless, to approach a more comparable treatment group, we have estimated a propensity score, capturing likelihood of switching to district-based elections as a function of city-level demographics. In Appendix Figure A5 we repeat our main analysis on a subset of outcomes using inverse probability weighting. Results are similar to our main results and in some cases more pronounced.

Finally, in light of recently highlighted concerns around two-way fixed effects models in difference-in-differences settings with staggered treatment rollout, we adopt a two-stage difference-in-differences approach proposed by Gardner (2022). Results are reported in Appendix Fig. A6. Again, results are relatively similar to our main results, with the potential exception of the two outcomes based on neighborhood composition, where under this approach we find no effect of district-based elections.

TABLE A1 *Warning Letters and Lawsuits Filed Against At-Large California Cities*

Year	Letters Sent	Lawsuits Filed
2004	0	1
2009	1	0
2010	1	1
2011	1	1
2012	1	1
2013	3	2
2014	1	4
2015	9	2
2016	7	3
2017	38	1
2018	26	1
2019	7	2

TABLE A2 *Summary Statistics at City Level, Split by Districting Status*

	Districted during Sample Period?		
	Never Dist.	Switch to Dist.	Always Dist.
N	322.00 (68.51%)	116.00 (24.68%)	32.00 (6.81%)
Total Pop. (1000s)	34.16 (55.22)	72.17 (52.39)	205.85 (193.51)
Share Over 18	0.76 (0.06)	0.74 (0.05)	0.73 (0.05)
Share Over 65	0.14 (0.07)	0.12 (0.05)	0.10 (0.02)
Share Renter Occ. Housing	0.37 (0.14)	0.37 (0.10)	0.44 (0.08)
Share Inc > 2x Pov.	0.67 (0.18)	0.67 (0.13)	0.61 (0.13)
Share AAPI (CVAP)	0.11 (0.13)	0.10 (0.10)	0.13 (0.09)
Share Black (CVAP)	0.04 (0.07)	0.05 (0.05)	0.09 (0.07)
Share White (CVAP)	0.57 (0.27)	0.56 (0.18)	0.43 (0.17)
Share Hisp. (CVAP)	0.26 (0.25)	0.27 (0.15)	0.34 (0.20)

Notes: Table presents city-level means of variables listed on the left, with standard deviations in parentheses. All variables come from 2010 Census data. Sample period is from 2008-2020. “Never dist.” are cities that never held district-based elections during (or before) that sample period. “Always dist.” had district-based elections during the entire time period. “Switch to dist.” are cities that adopted district-based elections between 2008 and 2020.

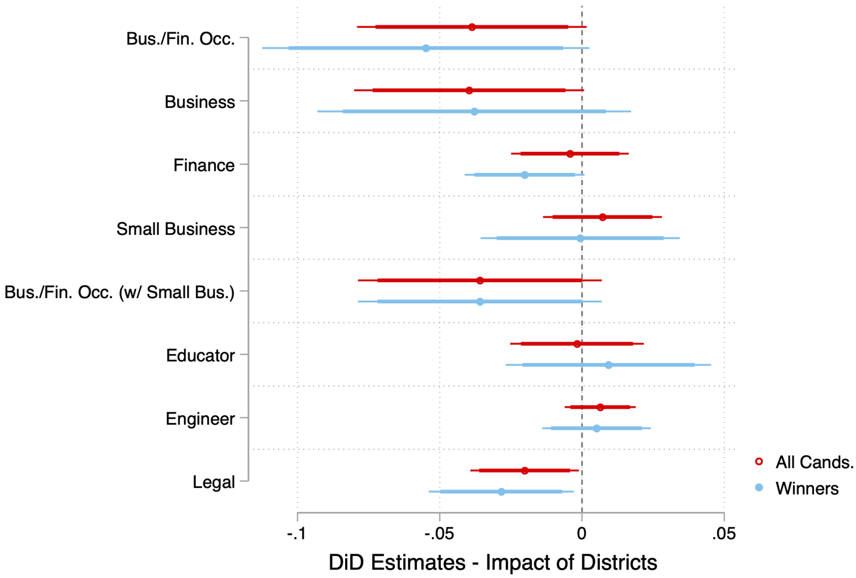
TABLE A3 *Category table with substrings and examples*

Category	**Substrings that define category**	**Randomly selected examples**	**Share**
Business	business, owner, entrep, executive; EXCLUDE: smallbusiness	Business Owner/Banker, Retired Business Man, Businessman	0.25
Finance/Invest.	banking, investment, investor, capitalist, finance, accounting, realtor, realestate	Investment Adviser Representative, Investment Consultant, Finance Executive	0.03
Small Business	smallbusiness	Small Business Owner, Small Business Owner, Small Business Owner	0.05
Engineer	engineer	Civil Engineer, Engineer, Engineering Geologist	0.07
Educator	educator, teacher, professor, instructor, lecturer	Educator/Business Owner, Archaeologist/Educator/Scientist, Teacher	0.02
Legal	lawyer, attorney, litigator, judge	Attorney/Businessman, Employment Law Attorney, Lawyer/Planning Commissioner	0.04

Notes: In our paper, "business/finance" related occupations consist of those listed in the "business" category and the "finance/invest." category noted above. The second column indicates the substrings used to identify occupations in each category. The third column reports, based on a random sorting of the data, the first three randomly selected ballot designations within a given category. The final column displays the share of candidates tagged with each occupational category.

Appendix Figure A1 provides more evidence on shifts by occupational background, including both some decomposition of our business/finance category and also several other frequently occurring categories. In particular, other common occupational categories are: educator, engineer, and legal. (See Appendix Table A3 for definitions and examples of each.) We observe no change in candidate entry or election of educators or engineers; we do observe a decline in the election of individuals in law-related occupations (lawyers, judges, etc.).

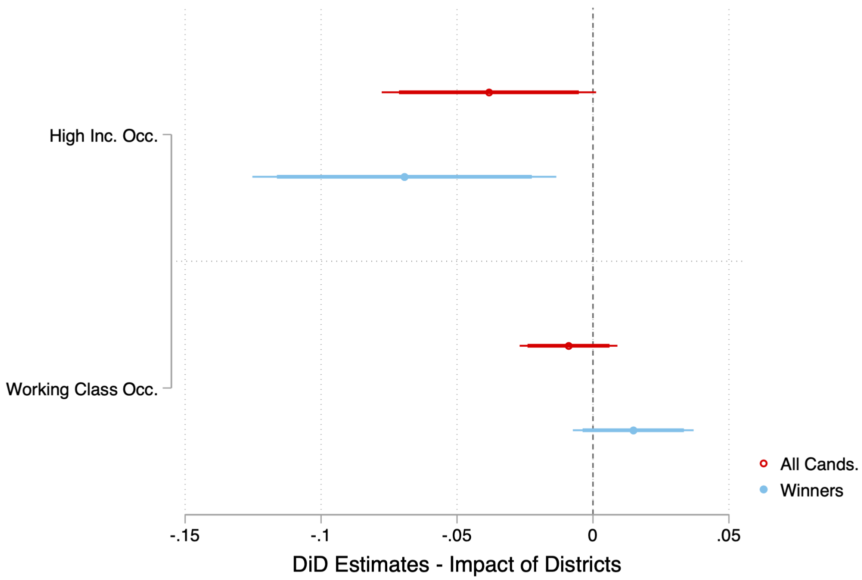
Figure A1. Difference-in-Difference Analysis, Additional Detail on Occupational Categories



Notes: Results reported here are drawn from specification identical to main specification, except that we add controls for county-by-year level unemployment rate and a housing price index.

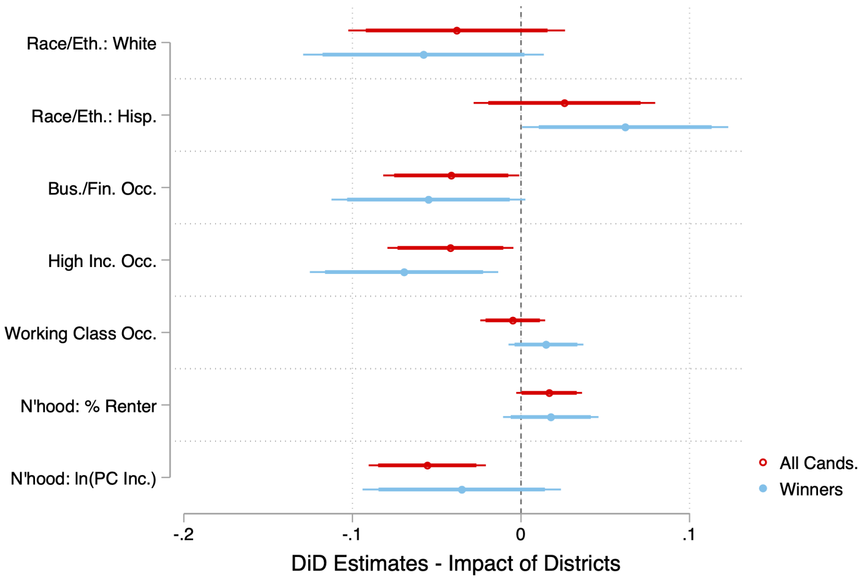
Appendix Figure A2 reports results from our alternative coding of occupations, using a large-language model to categorize ballot designations as “high earning” occupations or “working class” occupations (as described above). We observe a significant decline in the election of individuals categorized as “high earning”; we observe an increase, but not significant, in the election of individuals categorized as “working class”.

Figure A2. Difference-in-Difference Analysis, Occupational Categories as Coded by a Large-Language Model



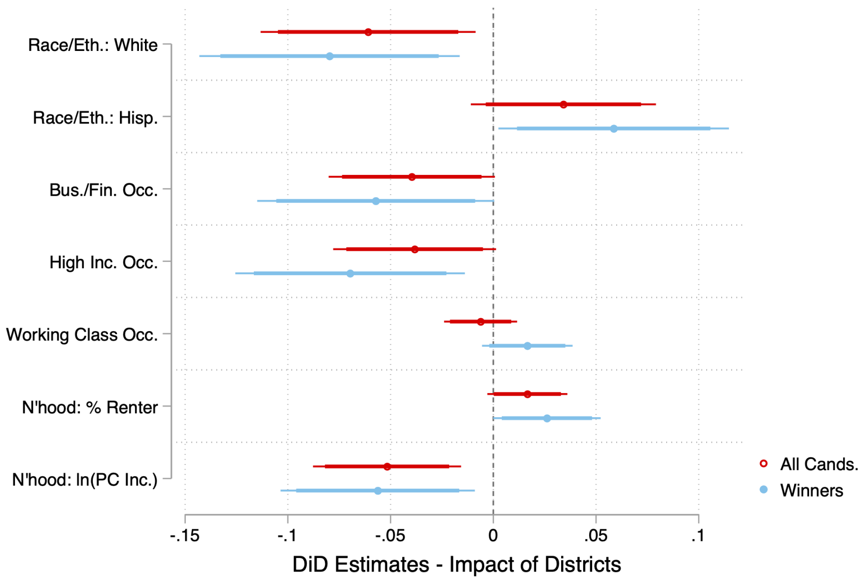
Notes: Results reported here use the main difference-in-differences specification outlined in the main text of our paper. Our outcomes are measures of the share of candidates in an election-year who have “High Income” or “Working class” occupations, based on coding of ballot designations from a large-language model.

Figure A3. Difference-in-Difference Analysis, Main Outcomes: Restricting to Election-Year Observations Where Relevant Variable is Identified for All Winning Candidates



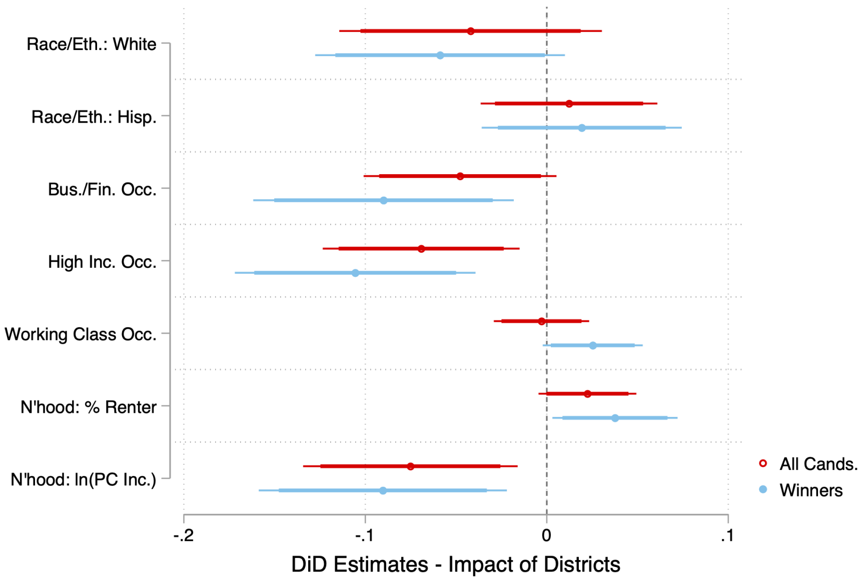
Notes: Results reported here are drawn from specification identical to main specification, except that we add controls for county-by-year level unemployment rate and a housing price index.

Figure A4. Difference-in-Difference Analysis, Main Outcomes: Adding Time-Varying Controls



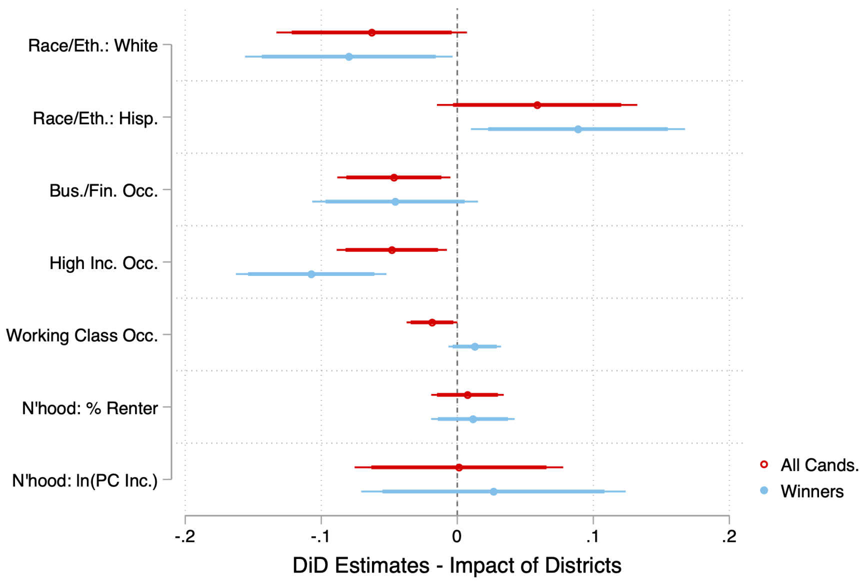
Notes: Results reported here are drawn from specification identical to main specification, except that we add controls for county-by-year level unemployment rate and a housing price index.

Figure A5. Difference-in-Difference Analysis: Propensity-Score Weighted



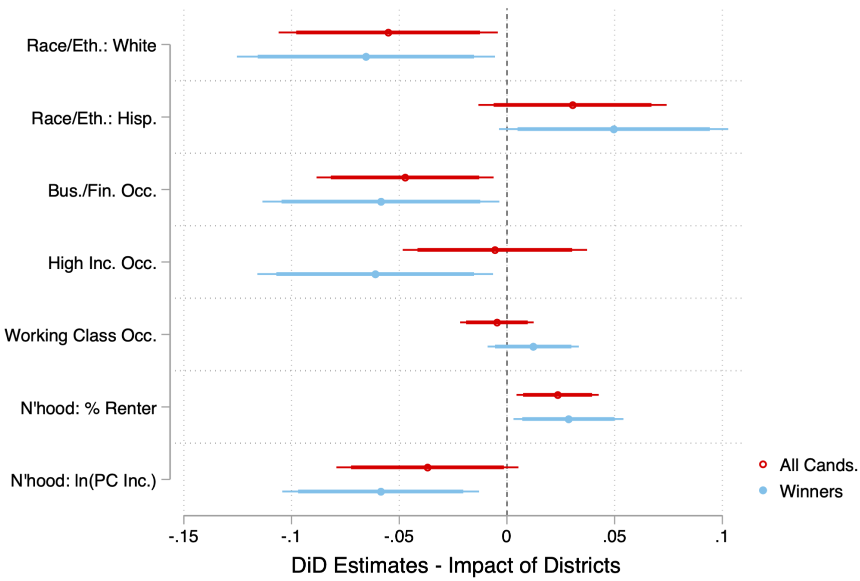
Notes: Results reported here are drawn from specification identical to main specification, except that we inverse-weight observations by propensity of being treated. Propensity score is calculated based on city race/ethnic composition (based on CVAP), dummies for quinitiles in population, renter share, and share of population earning over 2x the poverty line.

Figure A6. Difference-in-Difference Analysis: Two-Stage Difference-in-Differences



Notes: Results here use the two-stage difference-in-differences approach of Gardner (2022).

Figure A7. Difference-in-Difference Analysis: Including Always Districted Cities in Sample



Notes: Results here replicate main analysis, but include always-districted cities in the sample.

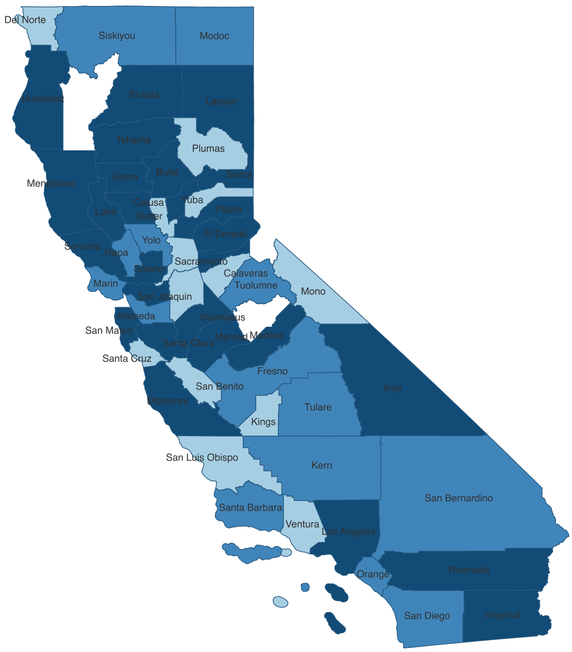
Matching Candidates to Voter Files

The process of matching candidates to voter files by name inevitably leads to some unmatched candidates, as in some cases there is no unique match across the two datasets. Specifically, candidates are often matched to mulitple observations in the voter files; if there is a candidate named "John Smith" in Richmond, CA, but there are multiple registered voters with that name in that city, we cannot identify a unique match.[1] We do however, identify matches for roughly ten thousand candidates (or 70%, after dropping candidates from cities that are districted during our entire sample period, as those cities are not included in our analysis).

To assess whether there is any systematic relationship between candidates matched vs. not matched, we provide two figures. First, we map match rates by counties, simply to assess whether there are clear regional patterns in where we were more successful in matching candidates. We do not see any clear patterns. Second, we run a regression at the city-level to assess whether ability to match is related to city-level characteristics. We observe no correlations on that front, other than a slightly lower match rate in counties with a higher AAPI population share. At the candidate-level, candidates who we identified in voter files are more likely to have won their elections. The same is true for candidates for whom we identified race/ethnicity identifiers for; we find this to be unsurprising, as candidates were largely identified via photos and photos were more available for successful candidates – either because they appear in the news or because they run multiple campaigns.

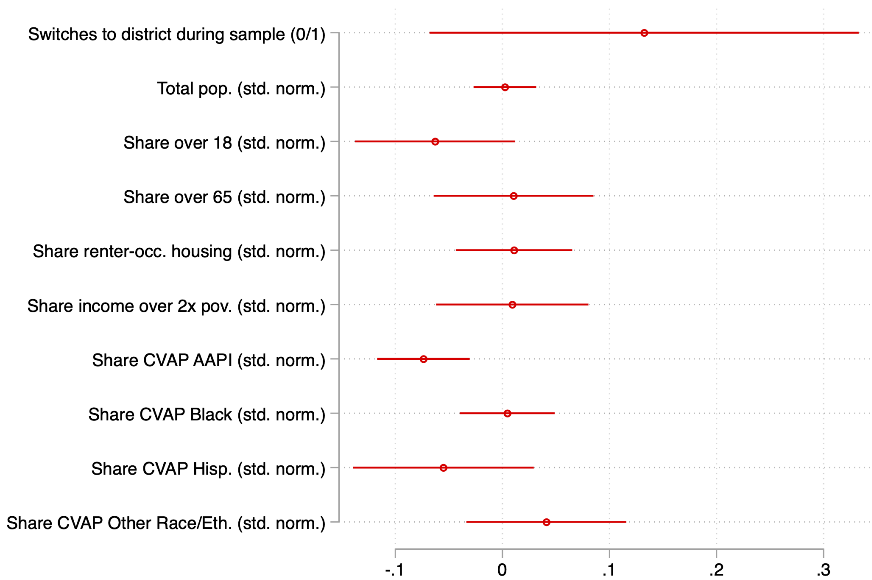
[1]This situation is a larger driver of non-matched candidates than candidates with no match in the voter files. Candidates are required to be registered voters, which helps ensure there should be someone to match to in the voter file.

Figure A8. Plotting regional differences in success of matching candidates to voter file



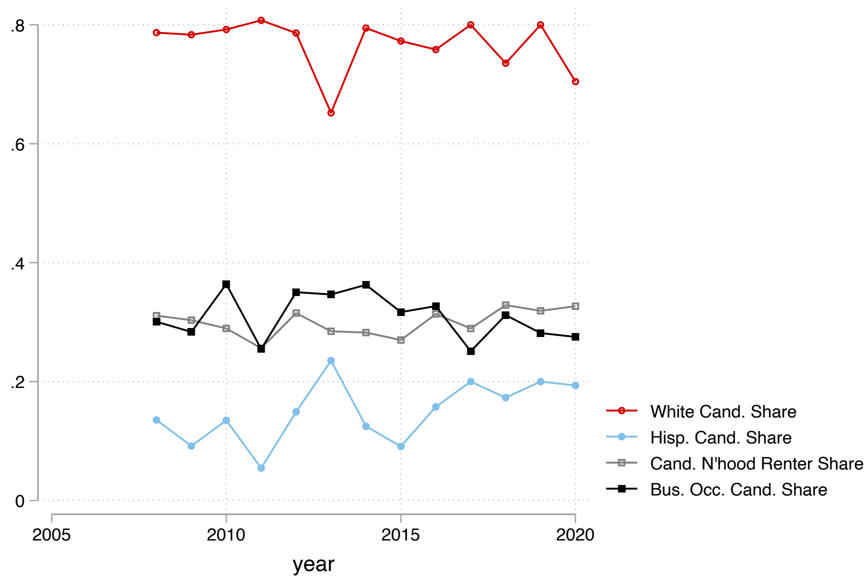
Notes: Map depicts areas (counties) with in top, middle, and bottom tercile of match rates between candidate files and voter registration files. A perfect match rate would imply that every candidate in the elections data was successfully matched to the voter files. Dark blue is the top tercile (mean match rate = 0.8), medium blue is the middle tercile (mean match rate = 0.68), and light blue is the bottom tercile (mean match rate = 0.58).

Figure A9. *Relationship between city-level candidate match rate and city characteristics*



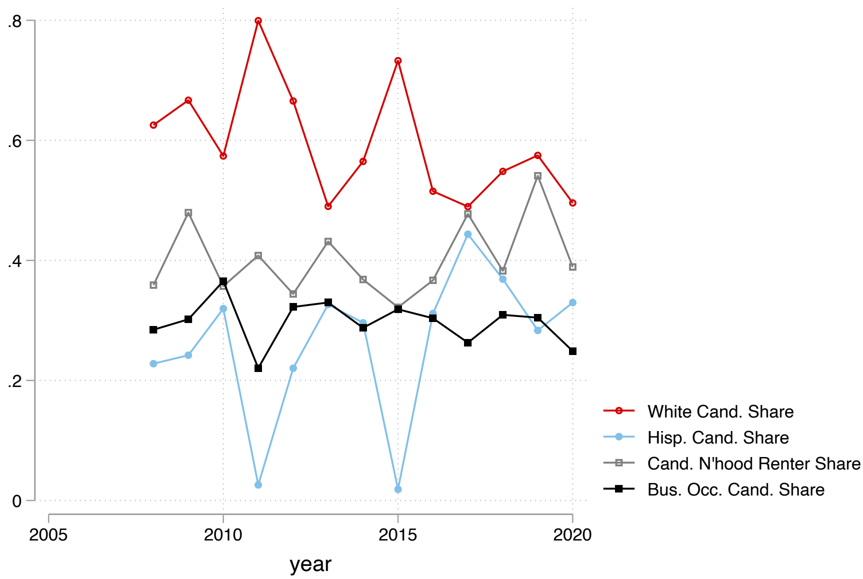
Notes: Plotting coefficients from a single regression of city-level candidate-match rate on the variables listed on the left. All variables, other than "switches to.." have been standard normalized, such that they all have mean of zero and standard deviation of one.

Figure A10. Cities that switch to district-based elections during sample period: Averages of main outcomes across time



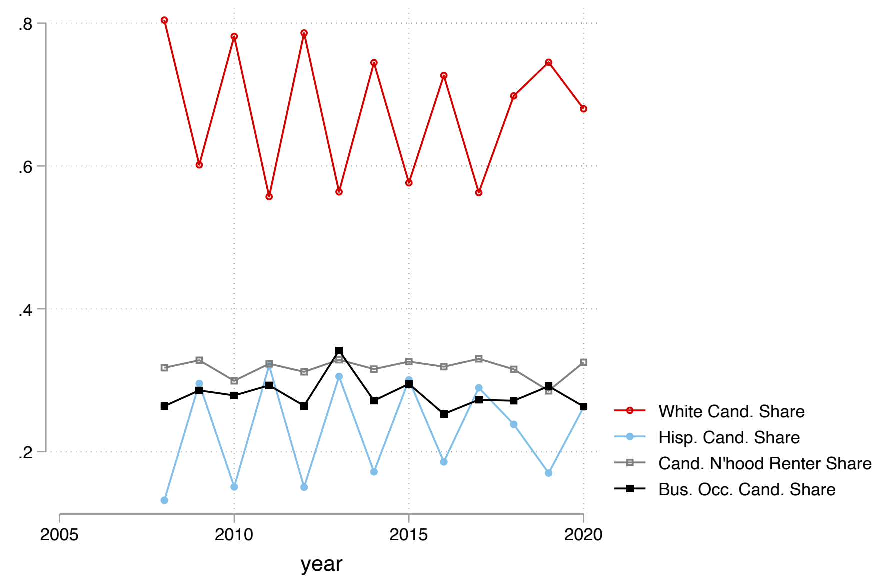
Notes: This figure plots simple year-by-year averages of shares of candidates with the listed characteristics.

Figure A11. Cities that hold district-based elections throughout sample period: Averages of main outcomes across time



Notes: This figure plots simple year-by-year averages of shares of candidates with the listed characteristics.

Figure A12. Cities that never hold district-based elections during sample period: Averages of main outcomes across time



Notes: This figure plots simple year-by-year averages of shares of candidates with the listed characteristics.

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