

# **EXHIBIT F**

# Declaration on Congressional Plan C2333

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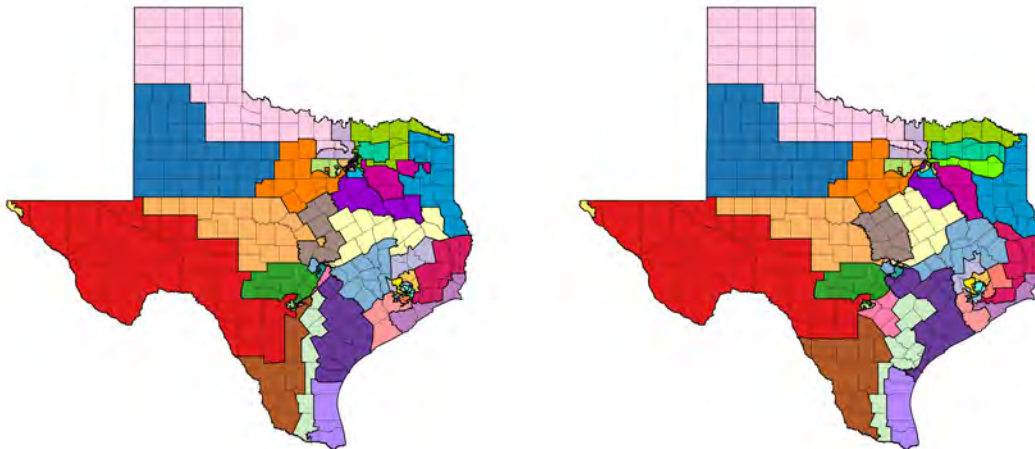
August 25, 2025

I am a Professor of Data Science and Computer Science and the Director of the Data and Democracy Research Initiative at the University of Chicago. I refer to my previous reports for a discussion of my qualifications and prior testimony as an expert in the field of redistricting. I have attached an updated CV with this Declaration.

## 1 Summary

In this Declaration, I offer metrics and analysis for Texas Congressional Plan C2333, recently passed into law. I have examined evidence relating to the claims of overriding partisan motives for changes to the map, particularly as partisan aims relate to opportunity-to-elect for minority groups. I find that the map is dilutive of minority voting strength. I also find strong evidence that race data was used by the line-drawers in a manner consistent with demographic targets and/or as a proxy for partisanship. In my analysis, the changes are not consistent with the race-neutral pursuit of pure partisan aims.

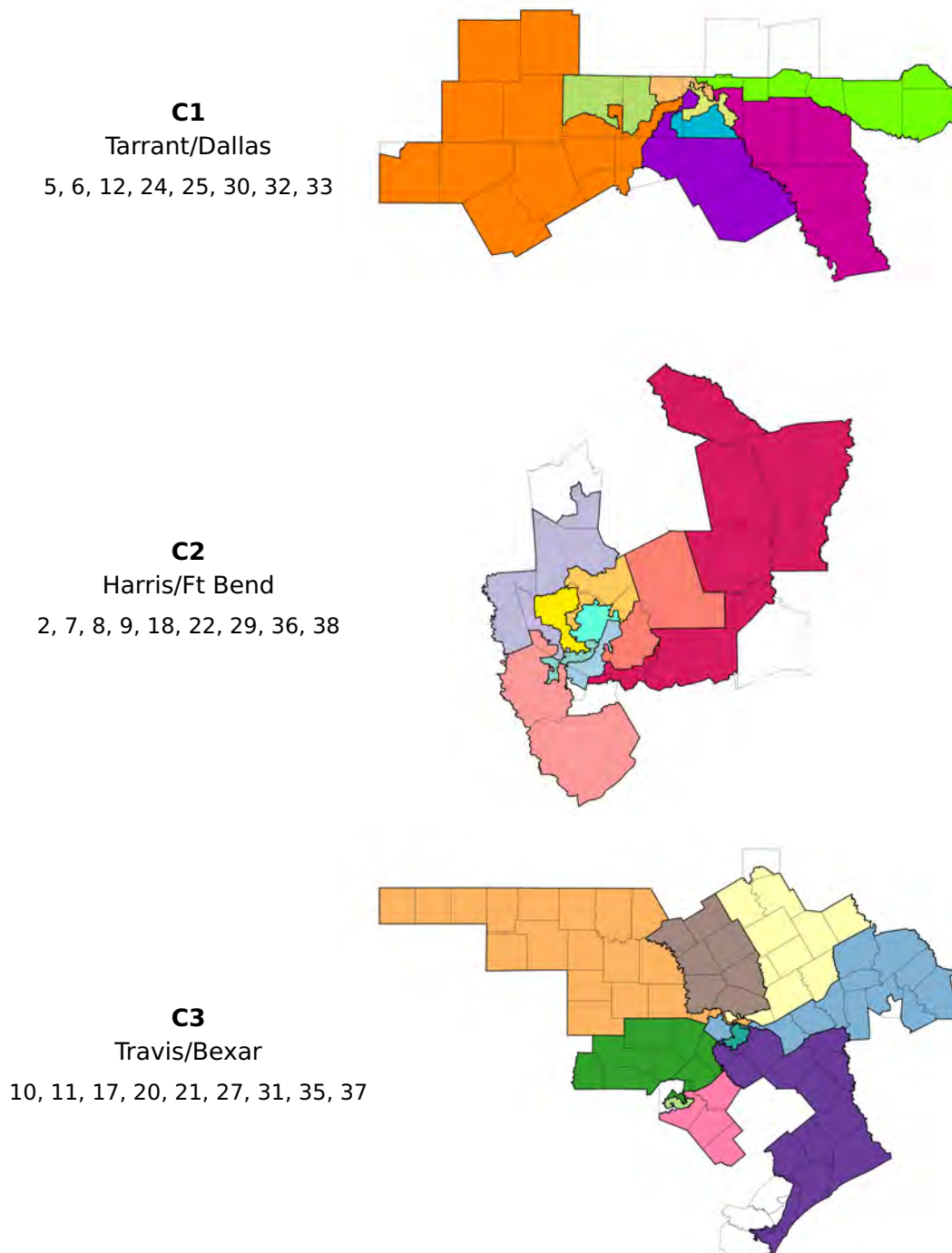
**Figure 1:** Plan C2193 (left) and Plan C2333 (right). Though the differences are hard to find at a glance, nearly every district has been changed.



I reprise my previous use of regional district clusters formed by groupings of the state's districts. The clusters in Tarrant/Dallas and Harris/Fort Bend have been adapted slightly from the previous report (reflecting the reconfiguration of the districts in C2333), and a third congressional cluster that includes districts from Travis County to Bexar

County has been added. The purpose of these clusters is to allow for localized analysis, including the comparison of C2333 districts to randomly generated alternative districts that span the same land area (§5.2).

**Figure 2:** The three district clusters C1, C2, C3.



## 2 Population shifts

Population growth alone was modest in the six Texas anchor counties since 2020, and in any event could not be a valid justification for this mid-decade redistricting, since the new map is population-balanced with respect to the 2020 data, just as the previous map was.<sup>1</sup>

Across the areas of the state covered by this Declaration, nearly all of the population growth in the recent past is accounted for by minority groups. People of color ("POC")—defined as those Texans who are either Hispanic or selected a non-White race in the Census or ACS—make up large majorities of the VAP and CVAP growth in each of the six urban counties that anchor the district clusters; in some cases, the POC growth actually exceeds the total growth, because non-Hispanic White population has declined over the same period.<sup>2</sup>

**Table 1:** Shifts in population according to American Community Survey 5-year rolling averages from five years apart, so that the survey years do not overlap. Statewide, people of color account for at least 94% of the growth, whether using voting age population or citizen voting age population. In clusters C1 and C2, the growth of POC communities has driven overall increases despite the decline of non-Hispanic White population. In cluster C3, POC make up about three-quarters of the growth.

Texas	ACS 2018 Count	2018 Pct	ACS 2023 Count	2023 Pct	Diff	Share of Diff
<b>TOTPOP</b>	27,885,181	—	29,640,343	—	1,755,162	—
<b>VAP</b>	20,592,495	—	22,157,813	—	1,565,318	—
NH White	9,483,944	46.1	9,571,408	43.2	87,464	5.6%
POC	11,108,551	53.9	12,586,404	56.8	1,477,853	94.4%
Black	2,482,337	12.1	2,706,261	12.2	223,924	14.3%
Hispanic	7,323,498	35.6	8,070,575	36.4	747,077	47.7%
Asian+PI	1,026,506	5.0	1,250,462	5.6	223,956	14.3%
AMIN	100,468	0.5	144,320	0.7	43,852	2.8%
<b>CVAP</b>	17,859,482	—	19,470,070	—	1,610,588	—
NH White	9,317,648	52.2	9,413,882	48.4	96,234	6.0%
POC	8,541,834	47.8	10,056,187	51.6	1,514,353	94.0%
Black	2,371,995	13.3	2,585,888	13.3	213,893	13.3%
Hispanic	5,243,696	29.4	6,088,062	31.3	844,366	52.4%
Asian+PI	664,736	3.7	846,133	4.3	181,397	11.3%
AMIN	88,931	0.5	115,161	0.6	26,230	1.6%

<sup>1</sup>Using the Census Bureau's Annual Estimates of the Population for Counties, we see a growth from 2020 to 2024 on the following scale, in millions: Tarrant 2.12 → 2.23; Dallas 2.61 → 2.66; Harris 4.74 → 5.01; Fort Bend 0.83 → 0.96; Travis 1.30 → 1.36; and Bexar 2.02 → 2.13.

<sup>2</sup>In order to present changes across five years, we compare ACS totals by race from the 5-year 2014–2018 tabulation and the 5-year 2019–2023 tabulation. The 2024 results are due to be released in September 2025. See Appendix A for more information on the use of ACS data.

Cluster C1 Tarrant/Dallas	ACS 2018 Count	2018 Pct	ACS 2023 Count	2023 Pct	Diff	Share of Diff
<b>TOTPOP</b>	5,894,695	—	6,218,577	—	323,882	—
<b>VAP</b>	4,351,844	—	4,648,999	—	297,155	—
NH White	2,150,102	49.4	2,124,567	45.7	−25,535	−8.6%
POC	2,201,818	50.6	2,524,541	54.3	322,723	108.6%
Black	724,257	16.6	797,856	17.2	73,599	24.8%
Hispanic	1,181,838	27.2	1,338,585	28.8	156,747	52.7%
Asian+PI	225,932	5.2	264,711	5.7	38,779	13.0%
AMIN	21,453	0.5	28,081	0.6	6,628	2.2%
<b>CVAP</b>	3,716,257	—	4,019,715	—	303,458	—
NH White	2,119,809	57.0	2,095,539	52.1	−24,270	−8.0%
POC	1,596,570	43.0	1,924,325	47.9	327,755	108.0%
Black	689,400	18.6	756,591	18.8	67,191	22.1%
Hispanic	697,446	18.8	876,997	21.8	179,551	59.1%
Asian+PI	143,859	3.9	172,906	4.3	29,047	9.6%
AMIN	18,764	0.5	21,124	0.5	2,360	0.8%

Cluster C2 Harris/Ft Bend	ACS 2018 Count	2018 Pct	ACS 2023 Count	2023 Pct	Diff	Share of Diff
<b>TOTPOP</b>	6,613,574	—	7,016,936	—	403,362	—
<b>VAP</b>	4,842,516	—	5,186,941	—	344,425	—
NH White	1,924,521	39.7	1,877,933	36.2	−46,588	−13.5%
POC	2,918,006	60.3	3,309,154	63.8	391,148	113.5%
Black	866,830	17.9	927,156	17.9	60,326	17.5%
Hispanic	1,610,687	33.3	1,810,847	34.9	200,160	58.1%
Asian+PI	385,330	8.0	445,137	8.6	59,807	17.4%
AMIN	18,664	0.4	36,454	0.7	17,790	5.2%
<b>CVAP</b>	3,981,269	—	4,333,929	—	352,660	—
NH White	1,863,834	46.8	1,825,623	42.1	−38,211	−10.8%
POC	2,117,514	53.2	2,508,372	57.9	390,858	110.8%
Black	823,280	20.7	881,559	20.3	58,279	16.5%
Hispanic	982,945	24.7	1,186,098	27.4	203,153	57.6%
Asian+PI	261,427	6.6	321,138	7.4	59,711	16.9%
AMIN	15,403	0.4	25,941	0.6	10,538	3.0%

Cluster C3 Travis/Bexar	ACS 2018 Count	2018 Pct	ACS 2023 Count	2023 Pct	Diff	Share of Diff
<b>TOTPOP</b>	6,558,301	—	7,059,781	—	501,480	—
<b>VAP</b>	4,963,506	—	5,410,656	—	447,150	—
NH White	2,506,440	50.5	2,621,277	48.4	114,837	25.7%
POC	2,457,075	49.5	2,789,430	51.6	332,355	74.3%
Black	423,116	8.5	459,057	8.5	35,941	8.0%
Hispanic	1,791,548	36.1	1,959,792	36.2	168,244	37.6%
Asian+PI	170,832	3.4	219,764	4.1	48,932	10.9%
AMIN	27,222	0.5	40,170	0.7	12,948	2.9%
<b>CVAP</b>	4,514,941	—	4,959,697	—	444,756	—
NH White	2,470,356	54.7	2,583,672	52.1	113,316	25.5%
POC	2,044,528	45.3	2,376,043	47.9	331,515	74.5%
Black	408,561	9.0	444,784	9.0	36,223	8.1%
Hispanic	1,458,983	32.3	1,641,653	33.1	182,670	41.1%
Asian+PI	106,628	2.4	143,277	2.9	36,649	8.2%
AMIN	24,074	0.5	33,441	0.7	9,367	2.1%

The tables for the six urban counties that anchor the district clusters are shown in the Appendix B.

### 3 Metrics

Next, we turn to metrics that relate to the traditional districting principles (TDPs). As a threshold matter, both one-person-one-vote population balance (with respect to total population from 2020) and district contiguity are in place. All plans have *de minimis* population deviation: one person top-to-bottom difference between districts. In the newest enacted plan (C2333), every district has 766,987 people according to the Decennial Census enumeration, except for CD 38, which has 766,986.

#### 3.1 Compactness, political boundaries, and core retention

The new C2333 plan is significantly more compact than the prior enacted plan C2193, and it splits fewer counties; with respect to the 2012 plan C2308, it is more compact by two measures but not by a third measure (known as the Reock score). However, the new plan splits hundreds of precincts, which will be discussed in more detail below.

For the compactness scores, Polsby-Popper and Reock are contour-based scores that were computed in the EPSG:32614 projected coordinate reference system and averaged over the districts in the plan. Cut edges is a measure of the "scissors complexity" of the plan: it counts the number of pairs of neighboring census blocks that receive different district assignments. Higher scores are considered better for Polsby-Popper and Reock, while lower scores are better for cut edges.

**Table 2:** Compactness, splitting, and core retention are presented through common quantitative metrics. Polsby-Popper and Reock are district-level scores; cut edges is a plan-wide score. Of the 254 counties in Texas, we first report the number that are split across multiple districts; then, the total number of pieces the counties are cut into. Splitting numbers for precincts at the time of plan adoption are highlighted. Core retention is calculated through population: it is the share of people in the 2020 Census that have the same district assignment in a given pair of plans.

	2012 Enacted	2021 Enacted	Plan C2333
Avg Polsby-Popper	0.1968	0.1886	0.2218
Avg Reock	0.3599	0.3322	0.3444
(Block) Cut Edges	20,976	21,355	17,618
County splits	36	30	31
County pieces	323	313	310
2024 Precinct splits	162	7	291
2022 Precinct splits	162	7	288
2020 Precinct splits	35	205	264
Core retention vs 2012	—	64.5%	54.2%
Core retention vs 2021	—	—	66.8%

**Note on district numbers.** A standard practice when issuing a new plan is to number the new districts so as to have maximum population overlap with the ones they are replacing. That way, an incumbent running in a certain district faces familiar voters.

C2333 uses optimal district numbering in 35 of its 38 districts. However, the numbering of CD 9, CD 18, and CD 29 has been shifted around in a cycle. The former CD 18 has its largest population overlap with the current CD 29. The number matching looks like this.

<u>C2333</u>		<u>C2193 (2021)</u>
New CD 9	↔	Prior CD 29
New CD 18	↔	Prior CD 9
New CD 29	↔	Prior CD 18

The reasons for this permutation of district numbers are not clear, but one effect is to make it somewhat harder to talk clearly about the changes to a particular district. The reconfiguration of CD 18 is explored further below in Appendix D.

## 3.2 Precinct splits

As far as I am aware, the state has not disclosed the use of any partisan data below the precinct level, while race data is available at the block level. Therefore the high number of precinct splits seen in Table 2 is more indicative of a focus on race than on partisanship.

It is important to note that precincts can and do change at between-census intervals; it is common practice for a districting plan to split precincts, and then for the precincts to be adjusted after the fact to better nest within districts. This is why the 2021 enacted plan splits a large number of 2020 precincts (205), but a much smaller number of 2022



precincts (7). However, the high level of precinct splitting in C2333 (291 splits) is notable because it is at odds with the stated goal of precision-targeted partisanship.

In the *Guide to 2021 Redistricting*, the Texas Legislative Council describes Election Data provided to the legislature within the Redistricting Data section of the report. They write: "Because election information is also required for analyzing a redistricting plan, a statewide election database compiled by legislative council staff provides county voting precinct boundaries, the results of statewide and many local primary, runoff, and general elections, and voter registration information by precinct for all counties. This election data is allocated to each census block within each voting precinct to allow for election data to be estimated for any district."

This account of allocating election data from precincts to blocks is typically referred to in spatial statistics as *proration*; the standard method would be to assign votes to blocks in proportion to their population (either TOTPOP, VAP, or CVAP). Thus, for instance, if a particular block has ten percent of the population of the precinct, it will be assigned ten percent of the vote totals. Thus every block within the precinct will have partisan shares equal to that of the precinct as a whole.<sup>3</sup>

When the allocation is proportional, no sub-precinct specificity is provided. This means that a redistricting plan created with overriding partisan intent would have no particular reason to split precincts. (In fact, each time a precinct is split, the plan faces a *loss* of precision in its partisan balance.) By contrast, race data does have block-level granularity coming from the Census, so a redistricting plan aiming to hit demographic targets would have a clear reason to split precincts.

## 4 Effective minority representation

The opportunity to be represented by candidates of choice has two components: minority groups must be able to both *nominate* preferred candidates through the primary/runoff process, and then to *elect* those preferred candidates in the general. To that end I am using the same scores of electoral alignment defined and explained in previous reports to analyze whether districts are likely to provide effective representation for minority groups.

There is no ambiguity about the partisan character of the districts in Table 3, as each one examined here either went for Democratic candidates in each of the eight general elections or went for Republicans every time. The use of primaries to decide whether minority groups have an opportunity to nominate preferred candidates is more gradated. When seven or eight of the eight primaries went to POC-preferred candidates, that indicates fairly clear ability to nominate. When only four of the eight do, that correlates well with control by White Democrats. The intermediate cases of five or six wins out of eight are less certain.

The clear conclusion of the effectiveness analysis shown here in Table 3 is that each of these three district clusters sees a net loss of one district that can reliably nominate and elect a POC-preferred candidate. The number of districts likely to elect White-preferred Democrats does not change: one in Tarrant/Dallas, one in Harris/Ft Bend, and a possible one in Travis/Bexar. That is, the creation of new majority-minority districts does not lead to increased electoral opportunity; the new plan effects a net loss of three districts that could previously reliably elect minority candidates of choice.

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<sup>3</sup>Beyond this interpretation of the TLC allocation process, this analysis assumes that the line-drawers used TLC electoral data and not ancillary sources like voter registration, commercial voter files, and so on.



**Table 3:** In each cluster, we use a mix of 8 primary/runoff and 8 general elections in which people of color had a clear candidate of choice. This table summarizes how many of the eight would have had that candidate of choice advance from the primary or get the most votes in the general. When only four of the eight primary and runoff elections advance the POC candidate of choice, it is typically the case that White Democrats control the district.

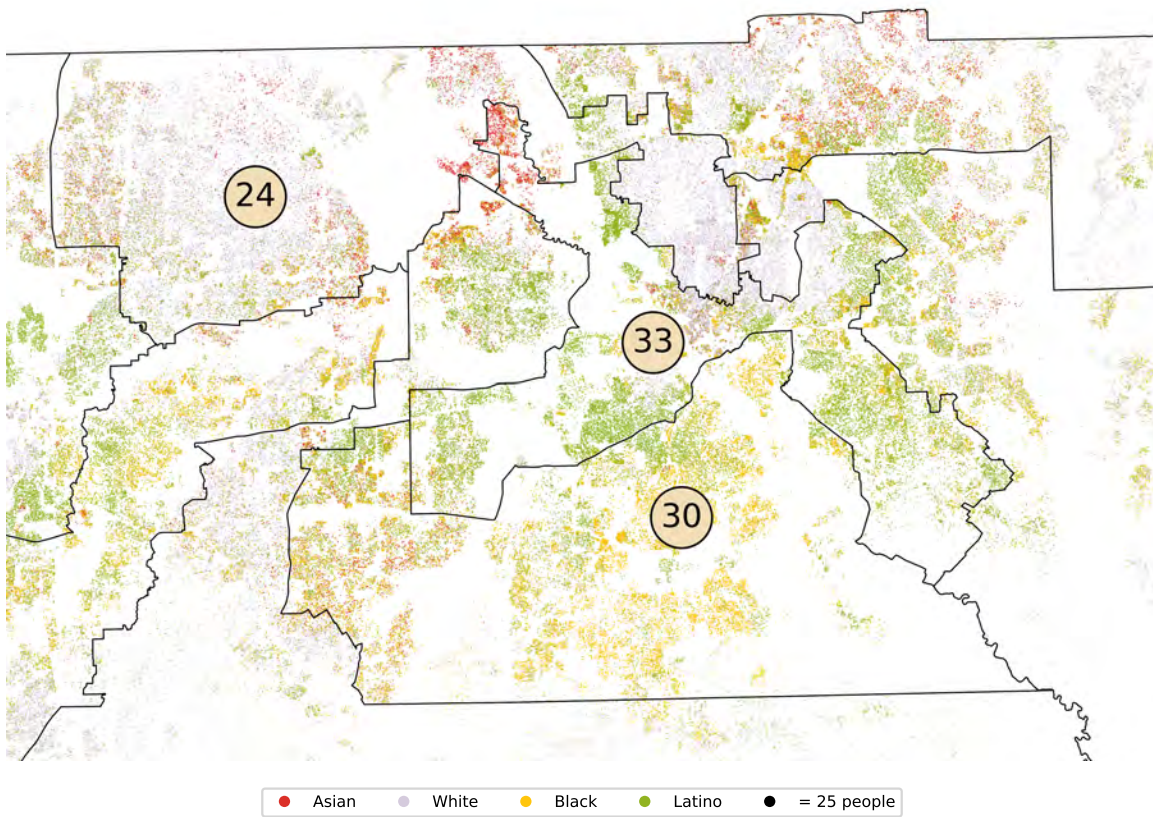
		C2193 (2021)			C2333 (new)		
		Primary	General	Effect	Primary	General	Effect
C1	CD 5	7/8	0/8	Republican	5/8	0/8	Republican
	CD 6	7/8	0/8	Republican	7/8	0/8	Republican
	CD 12	6/8	0/8	Republican	7/8	0/8	Republican
	CD 24	4/8	0/8	Republican	4/8	0/8	Republican
	CD 25	7/8	0/8	Republican	8/8	0/8	Republican
	CD 30	8/8	8/8	POC-preferred D	8/8	8/8	POC-preferred D
	CD 32	4/8	8/8	<b>White D</b>	5/8	0/8	<b>Republican</b>
	CD 33	8/8	8/8	<b>POC-preferred D</b>	4/8	8/8	<b>White D</b>
C2	CD 2	7/8	0/8	Republican	6/8	0/8	Republican
	CD 7	4/8	8/8	White D	4/8	8/8	White D
	CD 8	7/8	0/8	Republican	7/8	0/8	Republican
	CD 9	7/8	8/8	<b>POC-preferred D</b>	7/8	0/8	<b>Republican</b>
	CD 18	7/8	8/8	POC-preferred D	7/8	8/8	POC-preferred D
	CD 22	7/8	0/8	Republican	7/8	0/8	Republican
	CD 29	7/8	8/8	POC-preferred D	7/8	8/8	POC-preferred D
	CD 36	7/8	0/8	Republican	6/8	0/8	Republican
	CD 38	3/8	0/8	Republican	4/8	0/8	Republican
C3	CD 10	6/8	0/8	Republican	6/8	0/8	Republican
	CD 11	7/8	0/8	Republican	7/8	0/8	Republican
	CD 17	6/8	0/8	Republican	5/8	0/8	Republican
	CD 20	7/8	8/8	POC-preferred D	7/8	8/8	POC-preferred D
	CD 21	6/8	0/8	Republican	6/8	0/8	Republican
	CD 27	8/8	0/8	Republican	6/8	0/8	Republican
	CD 31	5/8	0/8	Republican	5/8	0/8	Republican
	CD 35	7/8	8/8	<b>POC-preferred D</b>	7/8	0/8	<b>Republican</b>
	CD 37	5/8	8/8	Democrat	6/8	8/8	Democrat

## 5 Racial vote dilution vs. partisanship

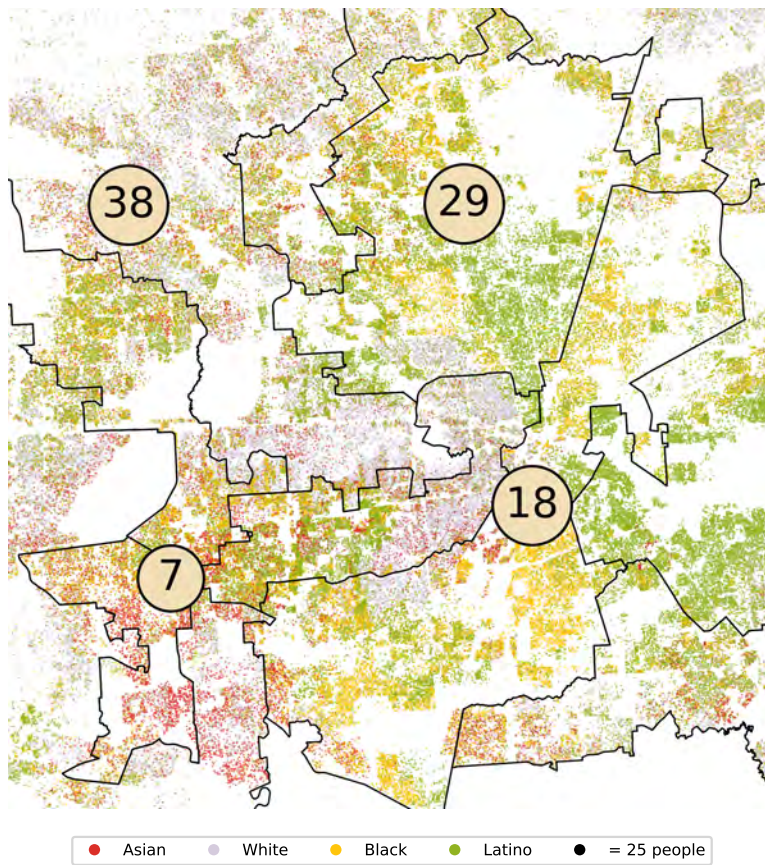
### 5.1 Dot density diagrams

In this section, I present dot density plots similar to those from earlier reports. To achieve the best visibility at the needed resolution, I have placed a dot for every 25 people from the Decennial Census data (TOTPOP). A green dot represents 25 people designated as Hispanic in the Census; amber dots show Black people; red dots show Asian and Pacific Islander people; and lavender dots show non-Hispanic White people. When district lines carve cleanly along racial lines in residential patterns, you can see one dot color predominate on one side of the line and a different set of colors on the other. This is visible, for instance, in CD 24, which dips down to encompass the heavily White enclaves of University Park and Highland Park while neatly avoiding Black and Latino neighborhoods of Dallas.

**Figure 3:** Dot density from Cluster C1 in Tarrant/Dallas shows that CD 24 is carefully designed to include White population and avoid pockets of minority groups.



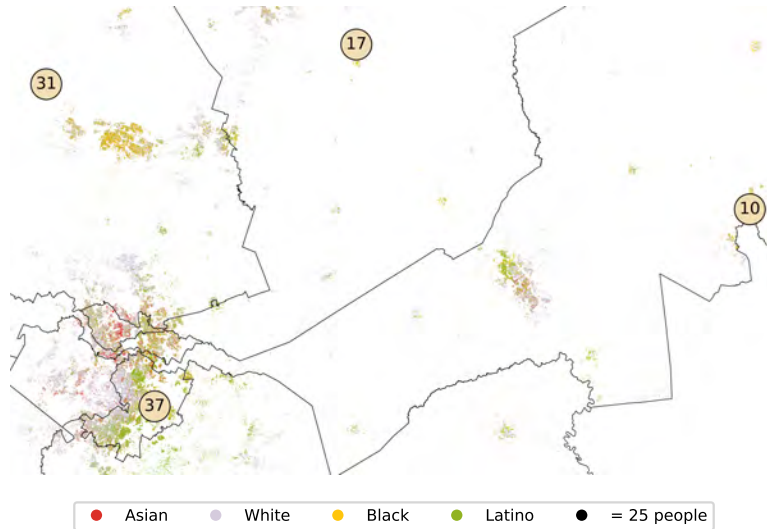
**Figure 4:** Dot density from Cluster C2 in Harris/Ft Bend shows patterns of sorting by race.



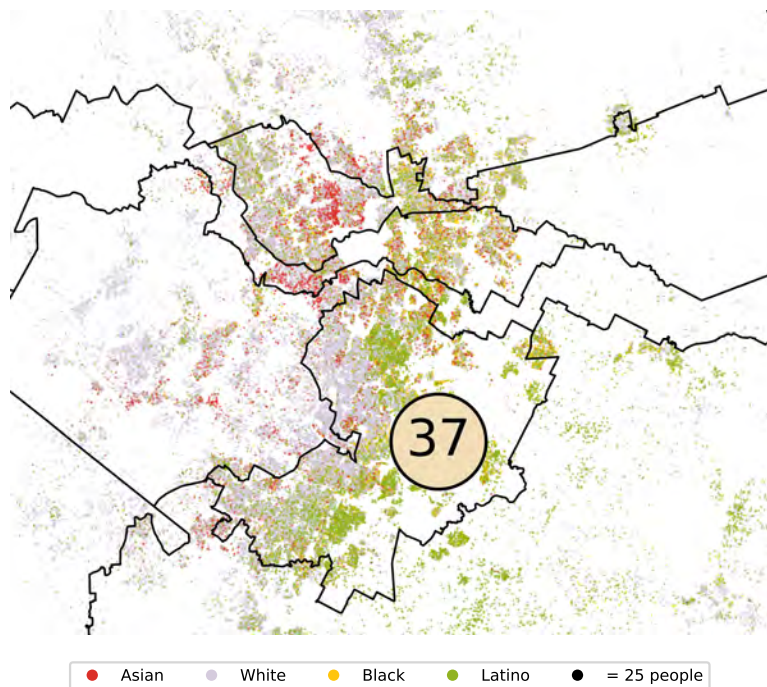
Similar dot density plots show detailed demographics for district clusters C2 (Figure 4) and C3 (Figures 5 and 6).



**Figure 5:** Dot density from Cluster C3 shows districts extending from rural surrounding counties to take strips of Travis County.



**Figure 6:** Close-up on Travis, showing the skinny layers of numerous districts that cut through the diverse areas in north Austin.



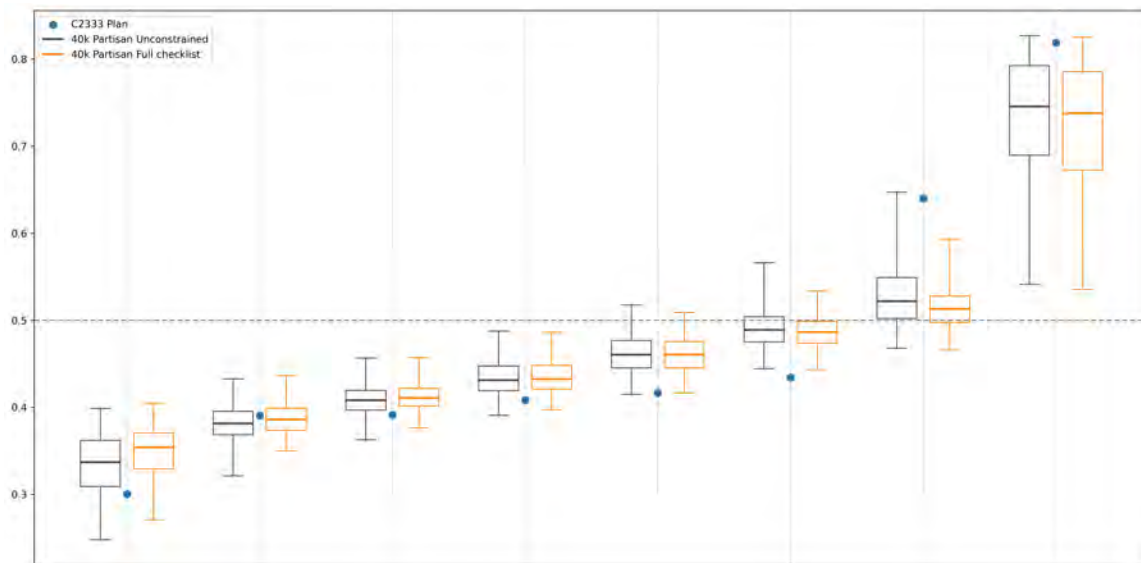
## 5.2 Assessing "packing and cracking" through outlier analysis

The use of algorithmically-generated alternative plans to assess the effects (and illuminate the intents) of proposed plans is an important emerging technique in redistricting analysis. My research group has created pioneering methods in this field. In this section I present evidence through the creation of comparison ensembles that race was heavily used by the line-drawers—possibly as a proxy for partisanship—in the creation of Plan C2333.

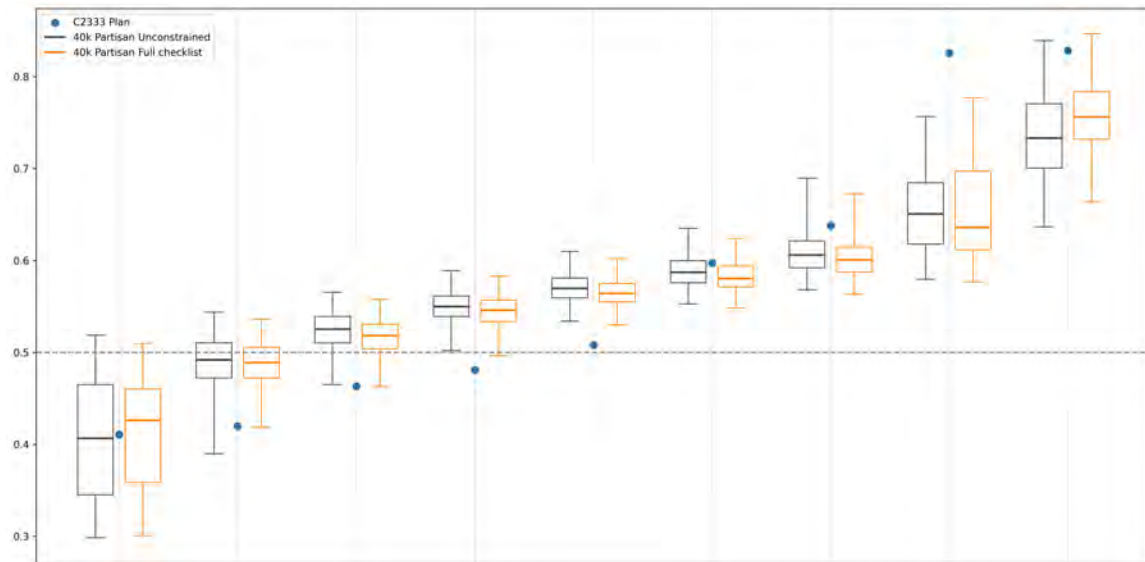
Figures 7–9 show that the racial composition of the districts is highly atypical of random plans whose partisan performance is at least as favorable to Republicans generally and to Donald Trump in particular. A checklist of traditional districting principles is incorporated into the methodology, and it only strengthens the finding that C2333 is an outlier in its racial composition. Details are provided in Appendix C.

Across the three clusters, the pattern is clear: as the expected demographic composition of the districts crosses 50% POC CVAP share, the state's plan has far lower levels of minority citizens than is found in the comparison plans. Where districts would be expected to be near even, one or more districts have sharply decreased minority share—this is what is informally known as *cracking*. In each case, the next district, which would be expected to have majority-POC CVAP, has notably elevated minority share—consistent with *packing*. This strongly suggests the use of race in crafting plans, above and beyond the mere consequences of pursuing partisan aims.

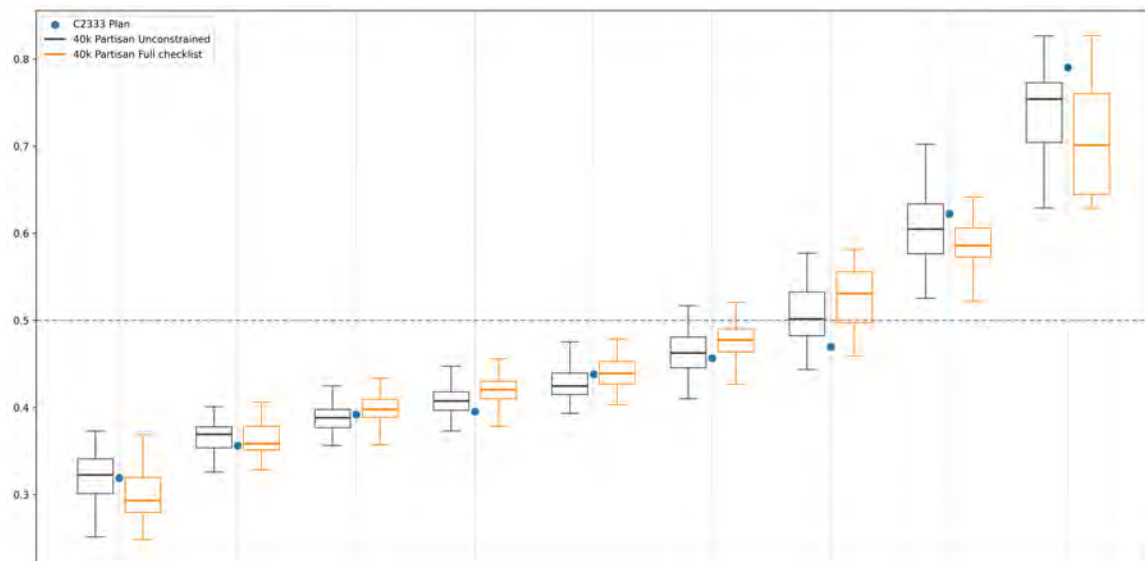
**Figure 7:** Cluster C1 (Tarrant/Dallas): The eight columns show the POC CVAP in districts of this cluster in C2333 as blue dots. The results of the algorithmic runs are shown in the boxplots in black, where the whiskers span from the 1st to the 99th percentile in each case. The orange boxplot shows the statistics once we have filtered the ensembles to only include plans that meet the full checklist of districting principles. We see that two of the eight districts—both where we would expect districts near the 50% mark—show that the POC CVAP is outlyingly low. In the next district, it is outlyingly high. This is true of the entire unfiltered set of partisan-preferring plans, and is more stark when filtering for the full checklist.



**Figure 8:** Cluster C2 (Harris/Ft Bend): This time, four of nine districts—again, all with expected POC CVAP near 50%—have outlyingly low levels of minority citizens, while one is elevated to an outlying degree. Filtering by the full checklist of TDPs does not change this finding.



**Figure 9:** Cluster C3 (Travis/Bexar): The signs of packing and cracking are less severe in this cluster, but the characteristic pattern is still present: one district near an expected 50% POC CVAP status has markedly diminished minority citizen share, while the next district is elevated to over 60%.



## 6 Conclusion

After presenting basic statistics for population shifts and plan metrics, this Declaration offers tools for a localized study to disentangle the racial and partisan elements of the line-drawing decisions in Plan C2333. The main findings are as follows.

- **Population shifts.** In each of the three district clusters studied here, the population growth is driven by people of color. (§2)
- **Precinct splitting.** Precincts are split at a level nearly 50% higher than in the previous plan. As far as the state has disclosed, this precinct splitting can serve no partisan purpose and is consistent with primary attention to race data. (§3.2)
- **Effective opportunity-to-elect.** Meaningful electoral opportunity requires the ability to both nominate and elect candidates of choice, irrespective of whether demographic targets have been hit. Each of the three clusters has a net loss of one district whose electoral history provides a record of success for POC-preferred candidates in most primary and general elections, while leaving intact the number of districts likely to incline to White Democrats. (§4) Thus, despite driving the population growth, minority groups will see their voting strength further diluted by the new map.
- **Outlier analysis.** Patterns characteristic of packing and cracking include depression of minority CVAP in districts where around 50% share would be expected, accompanied by elevation of minority CVAP in districts expected to have well over 50% share. These patterns are present in each of the three clusters, especially in clusters C1 (Tarrant/Dallas) and C2 (Harris/Ft Bend). This is true when comparing to sets of tens of thousands of plans that match or exceed the partisanship of C2333, and it remains true whether or not a long checklist of traditional districting principles is incorporated. (§5.2)

Taken together, this evidence suggests that the C2333 plan uses race to achieve its ends and is dilutive of minority voting strength, beyond the mere consequences of intensified partisan gerrymandering.



## A ACS data

For most of this Declaration (particularly Table 4 and §5.2), CVAP is created by applying citizenship rates obtained at the tract level to the VAP in each census block. Details of this construction can be found in a white paper at <https://mggg.org/VAP-CVAP>.

In order to facilitate a comparison at a shorter interval than Decennial, §2 above and the supplemental tables in Appendix B below use the race categories native to the ACS because they cannot take advantage of the finer classification available in the Decennial data. Those values come directly from the 5-year ACS ending in 2018 and the 5-year ACS ending in 2023.

## B County population shifts

Tarrant	ACS 2018 Count	2018 Pct	ACS 2023 Count	2023 Pct	Diff	Share of Diff
<b>TOTPOP</b>	2,020,691	—	2,135,743	—	115,052	—
<b>VAP</b>	1,480,163	—	1,587,266	—	107,103	—
NH White	765,692	51.7	745,943	47.0	−19,749	−18.4%
POC	714,457	48.3	841,323	53.0	126,866	118.4%
Black	233,890	15.8	270,440	17.0	36,550	34.1%
Hispanic	369,559	25.0	426,679	26.9	57,120	53.4%
Asian+PI	85,671	5.8	101,298	6.4	15,627	14.6%
AMIN	7,585	0.5	8,858	0.6	1,273	1.2%
<b>CVAP</b>	1,300,114	—	1,401,301	—	101,187	—
NH White	755,037	58.1	733,670	52.4	−21,367	−21.1%
POC	545,055	41.9	667,631	47.6	122,576	121.1%
Black	219,969	16.9	253,785	18.1	33,816	33.4%
Hispanic	242,431	18.6	302,533	21.6	60,102	59.4%
Asian+PI	59,201	4.6	71,000	5.1	11,799	11.7%
AMIN	6,636	0.5	6,713	0.5	77	0.1%

Dallas	ACS 2018 Count	2018 Pct	ACS 2023 Count	2023 Pct	Diff	Share of Diff
<b>TOTPOP</b>	2,586,629	—	2,603,816	—	17,187	—
<b>VAP</b>	1,898,830	—	1,941,989	—	43,159	—
NH White	649,013	34.2	599,605	30.9	−49,408	−114.5%
POC	1,249,810	65.8	1,342,384	69.1	92,574	214.5%
Black	428,454	22.6	441,796	22.7	13,342	30.9%
Hispanic	667,201	35.1	713,554	36.7	46,353	107.4%
Asian+PI	124,963	6.6	139,870	7.2	14,907	34.6%
AMIN	7,219	0.4	13,567	0.7	6,348	14.7%
<b>CVAP</b>	1,494,377	—	1,558,943	—	64,566	—
NH White	633,838	42.4	587,592	37.7	−46,246	−71.6%
POC	860,530	57.6	971,351	62.3	110,821	171.6%
Black	408,678	27.3	420,104	26.9	11,426	17.7%
Hispanic	350,472	23.5	420,196	27.0	69,724	108.0%
Asian+PI	74,155	5.0	85,895	5.5	11,740	18.2%
AMIN	6,283	0.4	9,445	0.6	3,162	4.9%

Harris	ACS 2018 Count	2018 Pct	ACS 2023 Count	2023 Pct	Diff	Share of Diff
<b>TOTPOP</b>	4,602,652	—	4,758,579	—	155,927	—
<b>VAP</b>	3,362,261	—	3,515,154	—	152,893	—
NH White	1,121,829	33.4	1,059,575	30.1	−62,254	−40.7%
POC	2,240,423	66.6	2,455,578	69.9	215,155	140.7%
Black	640,438	19.0	674,901	19.2	34,463	22.5%
Hispanic	1,303,803	38.8	1,418,489	40.4	114,686	75.0%
Asian+PI	258,000	7.7	279,951	8.0	21,951	14.4%
AMIN	13,344	0.4	29,223	0.8	15,879	10.4%
<b>CVAP</b>	2,662,104	—	2,845,384	—	183,280	—
NH White	1,077,530	40.5	1,024,706	36.0	−52,824	−28.8%
POC	1,584,567	59.5	1,820,677	64.0	236,110	128.8%
Black	605,011	22.7	640,133	22.5	35,122	19.2%
Hispanic	774,189	29.1	902,084	31.7	127,895	69.8%
Asian+PI	171,859	6.5	200,519	7.0	28,660	15.6%
AMIN	11,119	0.4	19,981	0.7	8,862	4.8%

Fort Bend	ACS 2018 Count	2018 Pct	ACS 2023 Count	2023 Pct	Diff	Share of Diff
<b>TOTPOP</b>	739,133	—	859,721	—	120,588	—
<b>VAP</b>	533,693	—	628,018	—	94,325	—
NH White	188,623	35.3	195,500	31.1	6,877	7.3%
POC	345,074	64.7	432,518	68.9	87,444	92.7%
Black	109,692	20.6	130,531	20.8	20,839	22.1%
Hispanic	120,960	22.7	146,803	23.4	25,843	27.4%
Asian+PI	108,359	20.3	139,378	22.2	31,019	32.9%
AMIN	1,506	0.3	2,318	0.4	812	0.9%
<b>CVAP</b>	449,343	—	538,144	—	88,801	—
NH White	179,544	40.0	185,432	34.5	5,888	6.6%
POC	269,802	60.0	352,712	65.5	82,910	93.4%
Black	103,435	23.0	122,200	22.7	18,765	21.1%
Hispanic	85,223	19.0	112,735	20.9	27,512	31.0%
Asian+PI	75,797	16.9	103,601	19.3	27,804	31.3%
AMIN	1,422	0.3	1,900	0.4	478	0.5%

Travis	ACS 2018 Count	2018 Pct	ACS 2023 Count	2023 Pct	Diff	Share of Diff
<b>TOTPOP</b>	1,203,436	—	1,307,625	—	104,189	—
<b>VAP</b>	934,080	—	1,039,958	—	105,878	—
NH White	495,004	53.0	530,413	51.0	35,409	33.4%
POC	439,073	47.0	509,545	49.0	70,472	66.6%
Black	76,296	8.2	85,649	8.2	9,353	8.8%
Hispanic	281,757	30.2	307,907	29.6	26,150	24.7%
Asian+PI	65,208	7.0	82,345	7.9	17,137	16.2%
AMIN	5,257	0.6	7,309	0.7	2,052	1.9%
<b>CVAP</b>	806,571	—	921,600	—	115,029	—
NH White	482,741	59.9	516,314	56.0	33,573	29.2%
POC	323,822	40.1	405,286	44.0	81,464	70.8%
Black	71,686	8.9	81,030	8.8	9,344	8.1%
Hispanic	195,712	24.3	236,798	25.7	41,086	35.7%
Asian+PI	40,822	5.1	55,180	6.0	14,358	12.5%
AMIN	4,233	0.5	5,966	0.6	1,733	1.5%

Bexar	ACS 2018 Count	2018 Pct	ACS 2023 Count	2023 Pct	Diff	Share of Diff
<b>TOTPOP</b>	1,925,852	—	2,037,344	—	111,492	—
<b>VAP</b>	1,426,732	—	1,529,319	—	102,587	—
NH White	440,445	30.9	445,670	29.1	5225	5.1%
POC	986,287	69.1	1,083,649	70.9	97,362	94.9%
Black	109,912	7.7	119,779	7.8	9867	9.6%
Hispanic	814,132	57.1	874,254	57.2	60,122	58.6%
Asian+PI	45,142	3.2	54,064	3.5	8922	8.7%
AMIN	9,546	0.7	17,194	1.1	7648	7.5%
<b>CVAP</b>	1,287,758	—	1,392,898	—	105,140	—
NH White	431,330	33.5	438,465	31.5	7,135	6.8%
POC	856,428	66.5	954,433	68.5	98,005	93.2%
Black	106,462	8.3	116,886	8.4	10,424	9.9%
Hispanic	704,937	54.7	766,047	55.0	61,110	58.1%
Asian+PI	29,555	2.3	37,142	2.7	7,587	7.2%
AMIN	8,789	0.7	14,324	1.0	5,535	5.3%

## C Ensemble methods and "checklist" of factors

Some responses to the use of ensemble evidence in litigation have faulted expert work for using statewide analysis rather than focusing on particular districts; likewise, some ensemble analysis has been criticized for failing to take various relevant districting principles into account.

For instance, a fairly comprehensive list of possible principles to incorporate in comparative study of redistricting alternatives includes those mentioned by Justices Alito and Thomas in their *Alexander* opinions: compactness, contiguity, respect for political subdivisions, communities of interest, incumbency, partisanship, urban character, media sources, transportation networks, and least change from a preferred map.

With these remarks in mind, I have constructed extremely thorough methods in the current analysis to take nearly every one of this long list of principles into account in generating ensembles of comparator plans. Furthermore, those plans are not made on a statewide basis, but in clusters of Congressional districts that are regionally proximate to the district at hand. This is as close as one can reasonably get to studying districts individually: since redistricting is a fixed-sum game with respect to Census population, changing one district must necessarily change its the boundaries of its neighbors; manipulating a single district necessarily has consequences on those neighbors.

### District generation parameters.

- Contiguity is enforced throughout runs of the Markov chain recombination algorithm.<sup>4</sup> Population balance is enforced by requiring each step to leave districts within 1% of ideal population.<sup>5</sup>
- Compactness is favored through the use of spanning trees to draw districts. Spanning trees are selected using a Kruskal-style minimum spanning tree (MST) algorithm where initial weights are drawn uniformly from [0, 1].
- County integrity is favored through the use of a "surcharge" of 0.1 on the edge weights for edges whose endpoints lie in different counties.
- A additional surcharge of 0.2 is used to encourage integrity of COUSUBs, or county subdivisions. In Texas, these are Census County Subdivisions, loosely parallel to Minor Civil Divisions in states that are partitioned into townships. In general, COUSUBs will respect the boundaries of small municipalities to the extent possible, while dividing cities into pieces with "stable boundaries" and "recognizable names." This can help here as a proxy for municipality preservation, communities of interest, transit networks, and local media.
- Core retention with respect to the state's new plan is implemented with a surcharge of 0.2 on edges that span across two of the state's new enacted congressional districts.
- Partisanship favoring Republican candidates in general is accounted for with a score based on the number of Republican district wins across a set of 29 general elections:
  - SenG12 - PRSG12 - RRComm3G14 - GovG14 - AgCommG14 - SenG14 - LtGovG14
  - RRComm1G16 - PRSG16 - RRComm1G18 - LandCommG18 - LtGovG18 - CompG18

<sup>4</sup>Daryl DeFord, Moon Duchin, and Justin Solomon, *Recombination: A Family of Markov Chains for Redistricting*, Harvard Data Science Review **3**(1) (Winter 2021).

<sup>5</sup>The adequacy of this level of population balance for ensemble generation has been discussed at length elsewhere, including in earlier reports filed in this case.

- AGG18 - GovG18 - SenG18 - RRCComm1G20 - PRSG20 - SenG20 - AgCommG22 - ATGG22 - ComptrollerG22 - GOVG22 - LandCommG22 - LTGG22 - RRCComm1G22 - PRSG24 - RRCComm1G24 - SenG24

- Partisanship specific to the performance of Donald Trump is accounted for in two ways: counting the number of Trump district wins in three elections (2016, 2020, 2024) and by simply considering the most recent election, Pres2024.

I then perform heuristic optimization runs using the short bursts local search method studied by Cannon et al., launched from multiple starting points, where the objective function is either general Republican partisanship or specific Trump partisanship.<sup>6</sup> Hundreds of thousands of maps are generated in each congressional cluster. These are then combined into a single large collection, then reduced to a smaller set of maps by imposing the following filters.

### **Winnowing conditions.**

- Republican performance: Republicans overall have at least as many wins in each cluster as in C2333. For instance, out of a total of  $29 \cdot 8 = 232$  district-level contests in the C1 Tarrant/Dallas cluster, the number won by Republicans must be at least as high as in C2333.
- Trump performance: at least as many districts have a plurality win for Donald Trump from the 2024 election as in C2333. For instance, out of 8 districts in the C1 Tarrant/Dallas cluster, the number favoring Trump must be at least six, as in C2333.
- Urban/rural composition: no district differs by more than ten percentage points from its counterpart in C2333 in its urban vs. rural composition. This is accomplished by labeling each census block as urban or rural according to the block group it belongs to, which has that attribute assigned by the Census Bureau. The urban vs. rural balance is measured by the basis of the share of population belonging to urban block groups.
- Incumbency: the double-bunking of incumbents with respect to the address file provided by counsel is no greater than in C2333.

After filtering down to maps that meet all of these conditions, there are at least 40,000 maps left in each of the three district clusters. I finally sample 40,000 districting plans uniformly at random from the filtered ensembles and use those to generate the boxplots in Figures 7–9.

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<sup>6</sup>Sarah Cannon, Ari Goldbloom-Helzner, Varun Gupta, J.N. Matthews, and Bhushan Suwal, *Voting Rights, Markov Chains, and Optimization by Short Bursts*, *Methodology and Computing in Applied Probability* **25** (1): 1–38 (2023).

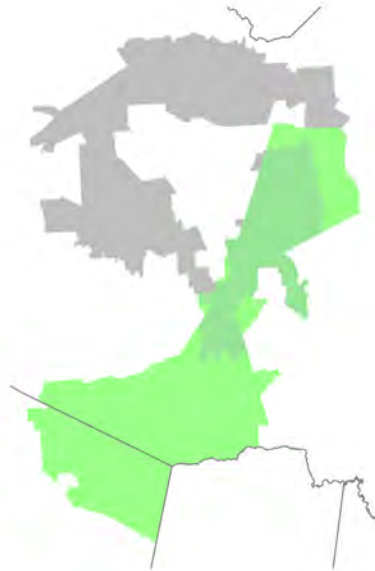
## D Changes to CD 18

Of the 766,987 census-enumerated people who were assigned to CD 18 in the last election, only 25.8% are assigned to the district now labeled CD 18. Over half (58.1%) now live in CD 29, and the others are scattered across districts 2, 7, and 38 (see Figure 11 and Table 4).

**Table 4:** The population dispersion from prior CD 18 is shown here, with more than twice as much going to new CD 29 as to new CD 18. The CVAP here is from the 5-year ACS ending in 2022.

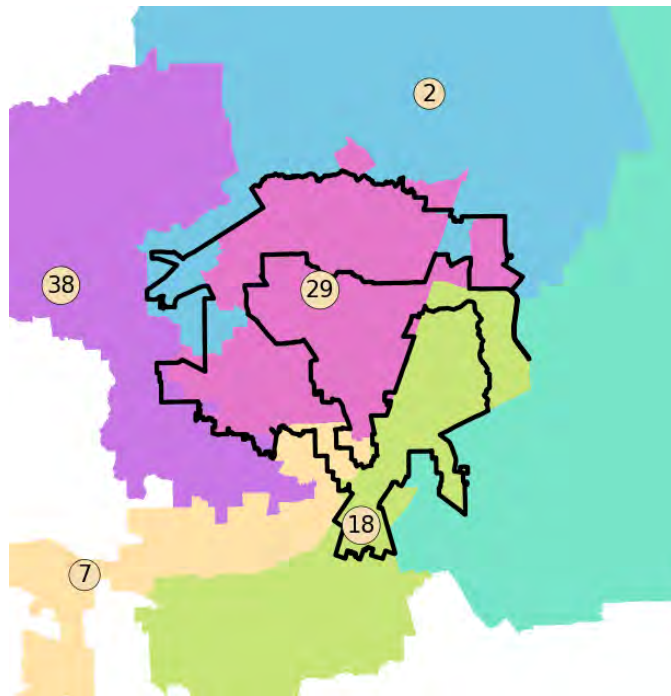
	<b>TOTPOP</b>	<b>VAP</b>	NH White	POC	<b>CVAP</b> 5-yr	NH White	POC
CD 2	59,105	43,558	8907	34,651	35,499.6	8589.7	26,909.8
CD 7	41,884	35,122	23,173	11,949	32,376.8	22,418.8	9957.9
CD 18	197,949	158,904	27,089	131,815	138,280.2	26,165.5	112,114.7
CD 29	445,987	322,052	52,116	269,936	253,806.4	50,865.3	202,941.1
CD 38	22,062	16,655	4277	12,378	11,563.9	4024.6	7539.3

**Figure 10:** New CD 18 (C2333) is shown in green, while prior CD 18 (2021 plan) is shown in gray.





**Figure 11:** The contours of prior CD 18 (as used in the 2024 election) are shown as a black outline, while the new districts from C2333 are shown in color.



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## Education

<b>University of Chicago</b> Mathematics	MS 1999, PhD 2005
<b>Harvard University</b> Mathematics and Women's Studies	BA 1998

## Appointments

<b>University of Chicago</b> Professor of Data Science, Computer Science, and the College <i>Director</i>   Data and Democracy Research Initiative	2025— 2025—
<b>Cornell University</b> Professor of Mathematics and Public Policy – <i>on leave</i> 2025–2026	2024–2025
<b>Santa Fe Institute</b> External Faculty	2024—
<b>Tufts University</b> John Dibiaggio Professor of Citizenship and Public Service Professor of Mathematics (previously Associate Professor, Assistant Professor) <i>Senior Fellow</i>   Jonathan M. Tisch College of Civic Life <i>Director</i>   Program in Science, Technology, & Society	2023–2024 2011–2024 2017— 2015–2021
<b>University of Michigan</b> Assistant Professor (postdoctoral)	2008–2011
<b>University of California, Davis</b> NSF VIGRE Postdoctoral Fellow	2005–2008

## Research Interests

Data science for democracy, computational social choice, geometry and redistricting.  
Science, technology, and society, computing and law, science policy, census data, privacy.  
Random walks and Markov chains, partition problems, networks, algorithmic fairness.  
Geometric group theory, geometric topology, hyperbolicity, metric geometry.

## Selected Awards & Distinctions

<b>Sloan Professor</b> , MSRI Program in Algorithms, Fairness, and Equity	Fall 2023
<b>Seelye Fellow</b> , University of Auckland Department of Mathematics	2023
<b>Radcliffe Fellow</b> - Evelyn Green Davis Fellowship	2018–2019
<b>Guggenheim Fellow</b>	2018
<b>Fellow of the American Mathematical Society</b>	elected 2017
<b>NSF C-ACCEL</b> (PI) - Harnessing the Data Revolution: Network science of Census data	2019–2020
<b>NSF grants</b> (PI) - CAREER grant and continuous grants from Topology/Geometric Analysis	2009–2024
<b>Professor of the Year</b> , Tufts Math Society	2012–2013
<b>AAUW Dissertation Fellowship</b>	2004–2005
<b>NSF Graduate Fellowship</b>	1998–2002
<b>Robert Fletcher Rogers Prize</b> (Harvard Mathematics)	1995–1996

## Applied and Interdisciplinary Publications &amp; Preprints

open access links included

**Political Geometry: Rethinking Redistricting in the U.S. with Math, Law, and Everything In Between**

25 chapters, 475 pages. Birkhäuser Books 2022. [Preprint online](#). (eds. Moon Duchin, Olivia Walch)  
see: [Introduction](#), [Compactness](#), [Communities of Interest](#), [Clustering](#), [Random Walks](#), [Ranked Choice Voting](#).

**Spanning tree methods for redistricting: New methods for sampling and validation**

SIAM Review, to appear. [Preprint](#). (with Sarah Cannon, Dana Randall, and Parker Rule)

**VoteKit: A Python package for computational social choice research**

Journal of Open Source Software **10**(109), 7477. [Open access](#).  
(with Christopher Donnay, Jack Gibson, Zach Glaser, Andrew Hong, Malavika Mukundan, and Jennfier Wang)

**The group perspective on fairness in multi-winner voting rules**

In submission. [Preprint](#). (with Kevin Quinn)

**Repetition effects in a sequential Monte Carlo sampler**

In submission. [Preprint](#). (with Sarah Cannon and Daryl DeFord)

**Proportionality for ranked voting, in theory and practice**

In submission. [Preprint](#). (with Gerdus Benade, Chris Donnay, and Thomas Weighill)

**Learning blocs and slates from ranked-choice ballots**

In submission. [Preprint](#). (with David Shmoys and Kris Tapp)

**Mapper graphs for voting analysis**

In preparation. [Preprint](#). (with Hazel Brenner, Emarie De La Nuez, and Jordan Phan)

**Ranked choice voting and proportional representation**

In preparation. [Preprint](#). (with Gerdus Benade, Ruth Buck, Dara Gold, and Thomas Weighill)

**Discrete geometry for electoral geography**

Political Geography, Volume 109, March 2024. [Open access](#). (with Bridget Eileen Tenner)

**Measuring segregation via analysis on graphs**

SIAM Journal on Matrix Analysis and Applications (SIMAX), **44** (1) 2023, 80–105. [Preprint version](#).  
(with James Murphy and Thomas Weighill)

**Implementing partisan symmetry: Problems and paradoxes**

Political Analysis **31** (3) 2023, 305–324. [Open access](#).  
(with Daryl DeFord, Natasha Dhamankar, Mackenzie McPike, Gabe Schoenbach, and Ki-Wan Sim)

**Redistricting for proportionality**

The Forum: A Journal of Applied Research in Contemporary Politics, Vol. 20, No. 3-4, Jan 2023, 371–393.  
[Open access](#). (with Gabe Schoenbach)

**Blind justice: Algorithms and neutrality in the case of redistricting**

Proceedings of 2nd ACM Symposium on Computer Science and Law (CS&Law), Nov 2022, 101–108. [Open access](#).  
(with Doug Spencer)

**Aggregating community maps**

ACM Conference on Advances in GIS (SIGSPATIAL), Nov 2022, 1–12. [Open access](#). (with Erin Chambers, Ranthony Edmonds, Parker Edwards, JN Matthews, Anthony Pizzimenti, Chanel Richardson, Parker Rule, and Ari Stern)

**Private numbers in public policy: Census, differential privacy, and redistricting**

Harvard Data Science Review, Spec. Iss. 2, June 2022. [Open access](#). (w Aloni Cohen, JN Matthews, Bhushan Suwal)

**The (homological) persistence of gerrymandering**

Foundations of Data Science, Vol 4, Issue 4 (2022): 581–622. [Preprint version](#). (w Tom Needham and Thomas Weighill)

**Recombination: A family of Markov chains for redistricting**

Harvard Data Science Review. Issue 3.1, Winter 2021. [Open access](#). (with Daryl DeFord and Justin Solomon)

**Census TopDown: The impact of differential privacy on redistricting**

2nd Symposium on Foundations of Responsible Computing (FORC 2021), 5:1–5:22. [Open access](#).  
(with Aloni Cohen, JN Matthews, and Bhushan Suwal)

**Computational Redistricting and the Voting Rights Act**

Election Law Journal, Volume 20, Number 4 (2021), 407–441. [Open access](#).  
(with Amariah Becker, Dara Gold, and Sam Hirsch)

**Models, Race, and the Law**

Yale Law Journal Forum, Vol. 130 (March 2021). [Open access](#). (with Doug Spencer)

**Clustering propensity: Segregation in networks**

[Preprint](#). (with Emilia Alvarez, Everett Meike, and Marshall Mueller; appendix by Tyler Piazza)

**Mathematics of nested districts: The case of Alaska**

Statistics and Public Policy. Vol 7, No 1 (2020), 39–51. [Preprint version](#).

(w/ Sophia Caldera, Daryl DeFord, Sam Gutekunst, & Cara Nix)

**A computational approach to measuring vote elasticity and competitiveness**

Statistics and Public Policy. Vol 7, No 1 (2020), 69–86. [Open access](#). (with Daryl DeFord and Justin Solomon)

**Redistricting reform in Virginia: Districting criteria in context**

Virginia Policy Review, Volume XII, Issue II, Spring 2019, 120–146. [Preprint version](#). (with Daryl DeFord)

**Locating the representational baseline: Republicans in Massachusetts**

Election Law Journal, Volume 18, Number 4, 2019, 388–401. [Open access](#).

(with Taissa Gladkova, Eugene Henninger-Voss, Ben Klingensmith, Heather Newman, and Hannah Wheelen)

**Geometry v. Gerrymandering**

*The Best Writing on Mathematics 2019*, ed. Mircea Pitici. Princeton University Press.

reprinted from *Scientific American*, November 2018, 48–53. [Magazine version](#).

**Gerrymandering metrics: How to measure? What's the baseline?**

Bulletin of the American Academy for Arts and Sciences, Vol. LXII, No. 2 (Winter 2018), 54–58. [Preprint version](#).

**Rebooting the mathematics of gerrymandering: How can geometry track with our political values?**

The Conversation (online magazine), October 2017. [Open access](#). (with Peter Levine)

**A formula goes to court: Partisan gerrymandering and the efficiency gap**

Notices of the American Mathematical Society **64** No. 9 (2017), 1020–1024. [Open access](#). (with Mira Bernstein)

**International mobility and U.S. mathematics**

Notices of the American Mathematical Society **64**, No. 7 (2017), 682–683. [Open access](#).

Pure Mathematics Publications & Preprints

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**Conjugation curvature for Cayley graphs**

Journal of Topology and Analysis, Vol 14, Number 02 (2022), 439–459. [Preprint version](#).

(with Assaf Bar-Natan and Robert Kropholler)

**You can hear the shape of a billiard table: Symbolic dynamics and rigidity for flat surfaces**

Commentarii Mathematici Helvetici, Vol 96, Issue 3 (2021), 421–463. [Preprint version](#).

(with Viveka Erlandsson, Christopher Leininger, and Chandrika Sadanand)

**Stars at infinity in Teichmüller space**

Geometriae Dedicata, Volume 213, 531–545 (2021). (with Nate Fisher) [Preprint version](#).

**The Heisenberg group is pan-rational**

Advances in Mathematics **346** (2019), 219–263. [Open access](#). (with Michael Shapiro)

**Random nilpotent groups I**

International Mathematics Research Notices, Vol. 2018, Issue 7 (2018), 1921–1953. [Open access](#).

(with Matthew Cordes, Yen Duong, Meng-Che Ho, and Ayla Sánchez)

**Hyperbolic groups**

in *Office Hours with a Geometric Group Theorist*, eds. M.Clay, D.Margalit, Princeton U Press (2017), 177–203. [Offprint](#).

**Counting in groups: Fine asymptotic geometry**

Notices of the American Mathematical Society **63**, No. 8 (2016), 871–874. [Open access](#).

**A sharper threshold for random groups at density one-half**

Groups, Geometry, and Dynamics **10**, No. 3 (2016), 985–1005. [Open access](#).

(with Katarzyna Jankiewicz, Shelby Kilmer, Samuel Lelièvre, John M. Mackay, and Ayla Sánchez)

**Equations in nilpotent groups**

Proceedings of the AMS **143** (2015), 4723–4731. [Open access](#). (with Hao Liang and Michael Shapiro)

**Statistical hyperbolicity in Teichmüller space**GAFA, Volume 24, Issue 3 (2014), 748–795. [Preprint version](#). (with Howard Masur and Spencer Dowdall)**Fine asymptotic geometry of the Heisenberg group**Indiana University Mathematics Journal 63 No. 3 (2014), 885–916. [Preprint version](#). (with Christopher Mooney)**Pushing fillings in right-angled Artin groups**JLMS, Vol 87, Issue 3 (2013), 663–688. [Preprint version](#). (w Aaron Abrams, Noel Brady, Pallavi Dani, Robert Young)**Spheres in the curve complex**Ahlfors–Bers VI, Contemp. Math. **590** (2013), 1–8. [Preprint version](#). (with Howard Masur and Spencer Dowdall)**The sprawl conjecture for convex bodies**Experimental Mathematics, Volume 22, Issue 2 (2013), 113–122. [Offprint](#). (w Samuel Lelièvre, Christopher Mooney)**Filling loops at infinity in the mapping class group**Michigan Math. J., Vol 61, Issue 4 (2012), 867–874. [Preprint version](#). (w Aaron Abrams, Noel Brady, Pallavi Dani, Robert Young)**The geometry of spheres in free abelian groups**Geom. Dedicata, Volume 161, Issue 1 (2012), 169–187. [Preprint version](#). (with Samuel Lelièvre and Christopher Mooney)**Statistical hyperbolicity in groups**Algebraic and Geometric Topology **12** (2012) 1–18. [Open access](#). (with Samuel Lelièvre and Christopher Mooney)**Length spectra and degeneration of flat metrics**Inventiones Math., Volume 182, Issue 2 (2010), 231–277. [Preprint version](#). (w Christopher Leininger, Kasra Rafi)**Divergence of geodesics in Teichmüller space and the mapping class group**Geometric and Functional Analysis, Volume 19, Issue 3 (2009), 722–742. [Preprint version](#). (with Kasra Rafi)**Curvature, stretchiness, and dynamics**In the Tradition of Ahlfors and Bers IV, Contemp. Math. **432** (2007), 19–30. [Offprint](#).**Geodesics track random walks in Teichmüller space**

PhD Dissertation, University of Chicago 2005.

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Interdisciplinary PhD course on computational social choice and applied modeling of democratic systems.

**Mathematics of Social Choice** | [sites.tufts.edu/socialchoice](https://sites.tufts.edu/socialchoice)

Voting theory, impossibility theorems, redistricting, theory of representative democracy, metrics of fairness.

*Have designed and taught variants at entry level and math-major level.***History of Mathematics** | [sites.tufts.edu/histmath](https://sites.tufts.edu/histmath)

Social history of mathematics, organized around episodes from antiquity to present. Themes include materials and technologies of creation and dissemination, axioms, authority, credibility, and professionalization. In-depth treatment of mathematical content from numeration to cardinal arithmetic to Galois theory.

**Reading Lab: Mathematical Models in Social Context** | [sites.tufts.edu/models](https://sites.tufts.edu/models)

One hr/wk discussion seminar of short but close reading on topics in mathematical modeling, including history of psychometrics; algorithmic bias; philosophy of statistics; problems of model explanation and interpretation.

**Reading Lab: Classification** | [sites.tufts.edu/classification](https://sites.tufts.edu/classification)

Discussion-based seminar of close reading on topics in classifications and taxonomies, including censuses; race and ethnicity; academic disciplines, definition in math and law; chemical elements; model organisms; sex and gender.

**Geometric Literacy**

Module-based graduate topics course. Modules have included:  $p$ -adic numbers, hyperbolic geometry, nilpotent geometry, Lie groups, convex geometry and analysis, the complex of curves, ergodic theory, the Gauss circle problem.

**Randomized Algorithms** (graduate/undergraduate topics course)

**Markov Chains** (graduate topics course)

**Teichmüller Theory** (graduate topics course)

**Fuchsian Groups** (graduate topics course)

**Continued Fractions and Geometric Coding** (undergraduate topics course)

**Mathematics for Elementary School Teachers** (inquiry-based course for pre-service teachers)

**Standard Courses**

Mathematical Modeling and Computation (with Python), Discrete Mathematics, Calculus I-II-III, Intro to Proofs, Linear Algebra, Complex Analysis, Differential Geometry, Abstract Algebra, Graduate Real Analysis

**Selected Talks and Lectures**

<b>Invited Talk</b> Autumn General Meeting of the American Philosophical Society, Philadelphia, PA	November 2024
<b>Plenary Lecture</b> SIAM Conference on Mathematics of Data Science (MDS24), Atlanta, GA	October 2024
<b>Plenary Lecture</b> Symposium on Computational Geometry (SoCG), Dallas, TX	June 2023
<b>Distinguished Plenary Lecture</b> 75th Anniversary Meeting of Canadian Mathematical Society, Ottawa, Ontario	June 2021 <i>online (COVID)</i>
<b>BMC/BAMC Public Lecture</b> Joint British Mathematics/Applied Mathematics Colloquium, Glasgow, Scotland	April 2021 <i>online (COVID)</i>
<b>AMS Einstein Public Lecture in Mathematics</b> Eastern Sectional Meeting of the AMS, Charlottesville, VA	April 2020 <i>postponed (COVID)</i>
<b>Gerald and Judith Porter Public Lecture</b> AMS-MAA-SIAM, Joint Mathematics Meetings, San Diego, CA	January 2018
<b>Mathematical Association of America Distinguished Lecture</b> MAA Carriage House, Washington, DC	October 2016
<b>American Mathematical Society Invited Address</b> AMS Eastern Sectional Meeting, Brunswick, ME	September 2016

**Named University Lectures**

- University Lecture, Data Science Distinguished Lecture   Cornell University	February 2024
- Martha Davenport Heard Lecture   Wellesley College	February 2024
- 47 Lecture   Pomona College	October 2023
- Seelye Public Lecture   University of Auckland, New Zealand	March 2023
- Lorne Campbell Lecture   Queen's University, Ontario	December 2022
- Plancherel Lecture   Université de Fribourg, Switzerland	October 2022
- Loeb Lectures in Mathematics   Washington University in St. Louis	April 2022
- Mathematics and Natural Sciences Divisional Lecture   Reed College	March 2022
- Parsons Lecture   UNC Asheville	October 2020
- Math, Stats, CS, and Society   Macalester College	October 2019
- MRC Public Lecture   Stanford University	May 2019
- Freedman Memorial Colloquium   Boston University	March 2019
- Julian Clancy Frazier Colloquium Lecture   U.S. Naval Academy	January 2019
- Barnett Lecture   University of Cincinnati	October 2018
- School of Science Colloquium Series   The College of New Jersey	March 2018
- Kieval Lecture   Cornell University	February 2018

**Math/Computer Science Department Colloquia**

- Northeastern University	Feb 2023	- Univ of Illinois - Chicago	Oct 2019
- University of Michigan	Sept 2022	- UC Berkeley	Sept 2018
- UC Berkeley	Apr 2022	- Brandeis-Harvard-MIT-NEU	Mar 2018
- Reed College	Dec 2020	- Northwestern University	Oct 2017
- Georgetown (CS)	Sept 2020	- University of Illinois	Sept 2017
- Santa Fe Institute	July 2020	- University of Utah	Aug 2017

**Minicourses**

- Modeling democracy (three hours)   Modern Math Workshop, Puerto Rico	October 2022
- Integer programming and combinatorial optimization (two talks)   Georgia Tech	May 2021

**Visiting Lectures**

- Law and Algorithms   Boston University	Spring 2024
- Normative, Legal, and Empirical Analyses of Discrimination   Yale Law School	Spring 2024
- Optimized Democracy   Harvard (CS)	Spring 2021, 2022, 2023, 2024
- Law of Democracy   Stanford Law School	Fall 2022
- A Democracy Initiative   Harvard Law School	Fall 2022
- Election Law   Harvard Law School   Yale Law School	Spring 2022
- Privacy, Policy, and the U.S. Census   University of Chicago (CS)	Spring 2022

**Data Science, Computer Science, Quantitative Social Science**

- Online Social Choice and Welfare Seminar	August 2023
- Data Matters Public Lecture   Data Science Institute, Brown University	April 2023
- Computational Social Choice Seminar   Center for Mathematical Social Science, Auckland	March 2023
- Societal Considerations and Applications   Simons Institute for the Theory of Computing	November 2022
- ACM Symposium on Computer Science and Law   Washington, DC	November 2022
- Econ/CS Seminar   Harvard	October 2022
- Can Algorithms Bend the Arc Towards Fairness?   Algorithmic Justice Project, UNM/SFI	March 2022
- Data Linkage Seminar   Massive Data Institute, McCourt School of Public Policy	August 2021
- Mechanism Design for Social Good (MD4SG) Colloquium   MD4SG Initiative	November 2020
- Data Science for Social Good (DS4SG) Workshop   Georgia Tech	November 2020
- Women in Data Science Conference   Microsoft Research New England	March 2020
- Quantitative Research Methods Workshop   Yale Center for the Study of American Politics	February 2020
- Societal Concerns in Algorithms and Data Analysis   Weizmann Institute	December 2018
- Quantitative Collaborative   University of Virginia	March 2018
- Quantitative Social Science   Dartmouth College	September 2017
- Data for Black Lives Conference   MIT	November 2017

**Law, Democracy, Political Science, Geography, Studies of Race and Gender**

- Data and Democracy Scholar Talk   Harris School, University of Chicago	April 2023
- Voting Rights Panel   Rothgerber Conference, University of Colorado Law School	April 2023
- Censuses and Racial Classification   COMPASS, University of Auckland	March 2023
- The Long 19th Amendment: Women, Voting, and American Democracy   Radcliffe Institute	Nov-Dec 2020
- "The New Math" for Civil Rights   Social Justice Speaker Series, Davidson College	November 2020
- Math, Law, and Racial Fairness   Justice Speaker Series, University of South Carolina	November 2020
- Voting Rights Conference   Northeastern Public Interest Law Program	September 2020
- Political Analysis Workshop   Indiana University	November 2019
- Program in Public Law Panel   Duke Law School	October 2019
- Redistricting 2021 Seminar   University of Chicago Institute of Politics	May 2019
- Geography of Redistricting Conference Keynote   Harvard Center for Geographic Analysis	May 2019
- Political Analytics Conference   Harvard University	November 2018
- Cyber Security, Law, and Society Alliance   Boston University	September 2018



- Clough Center for the Study of Constitutional Democracy | Boston College November 2017
- Tech/Law Colloquium Series | Cornell Tech November 2017
- Constitution Day Lecture | Rockefeller Center for Public Policy, Dartmouth College September 2017

### Science, Technology, and Society

- The Mathematics of Accountability | Sawyer Seminar, Anthropology, Johns Hopkins February 2020
- STS Circle | Harvard Kennedy School of Government September 2019
- Data, Classification, and Everyday Life Symposium | Rutgers Center for Cultural Analysis January 2019
- Science Studies Colloquium | UC San Diego January 2019
- Arthur Miller Lecture on Science and Ethics | MIT Program in Science, Tech, and Society November 2018

## Program Development

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Director, PI of **Data and Democracy Lab** (formerly MGGG Redistricting Lab) [mggg.org](http://mggg.org)

Multidisciplinary research lab with postdocs, research staff, and undergraduate researchers drawn from mathematics, computer science, geography, policy. Hosts law student externs. Provided public mapping support for roughly 140 localities after 2020 Census data released.

Support includes NSF, Crankstart Foundation, Democracy Fund, Kelson Foundation, Sloan Foundation, Thornburg Foundation, Arnold Foundation.

Director of **Structural Democracy Fellowship Program**

Fellowship program distributing research funding to initial cohort of 16 U.S. and international fellows. Tied to weekly online research seminar and special issue of Harvard Data Science Review, titled *Designing Democracy*.

Funded by gift from Crankstart Foundation.

Co-Founder, Program Director of **Science, Technology, and Society Program** [sts.tufts.edu](http://sts.tufts.edu)

Interdisciplinary program offering a major and minor, with ~40 affiliated faculty. Initiated popular weekly lunch seminar and developed Reading Lab courses on topics from Automation to Classification to Life to Energy.

### Program Organization

Semester Program in *Algorithms, Fairness, and Equity*, Fall 2023  
Mathematical Sciences Research Institute, Berkeley CA

Program hosted ~50 research members on topics connected to mechanism design, fair partitioning, and fair ML.

Short workshops and training programs

- Ranked Choice Modeling Session 2025 (2 days, planned for June 2025 at Cornell)
- Ranked Choice Modeling Session 2023 (1 day, 20 participants from think tanks and NGOs)
- GeoData Bootcamp 2020 (2 weeks, 20 students from around the country)
- Mapping Training 2020 (1 week, 30 students from around the country)
- Graphs and Networks Workshop 2020 (1 day, 500 live participants)
- Data for Election Administration 2019, 2021 (multi-day, dozens of administrators and scholars)

### Program Building Research and mentorship programs

- Voting Rights Data Institute 2018, 2019, 2023  
Six-week summer research programs hosting up to 52 undergraduate and graduate students, respectively, with dozens of visitors from math, CS, law, political science, geography, urban planning, and more.
- Polygonal Billiards Research Cluster 2017, Random Groups Research Cluster 2014  
Five-week intensive summer research programs for vertically integrated groups of 12-14 undergraduate, graduate, postdoctoral, and junior faculty researchers, combining experimental and theoretical work.

- Directed Reading Program and DRP Network [sites.google.com/view/drpf-network/](https://sites.google.com/view/drpf-network/)

Co-founded highly successful near-peer mentoring program in 2003 at UChicago. Now exists at >40 math departments as grad-student-run reading program with excellent outcomes for broadening participation in mathematics. Secured NSF grant to expand the program to more campuses and to fund social science research on outcomes.

### Graduate Advising in Mathematics

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Nate Fisher (PhD 2021), Sunrose Shrestha (PhD 2020), Ayla Sánchez (PhD 2017),  
Kevin Buckles (PhD 2015), Mai Mansouri (MS 2014)

*Co-advisor or outside committee member*

Chris Donnay (PhD 2024 Ohio State), Chris Coscia (PhD 2020 Dartmouth College)

### Postdoctoral Advising in Mathematics and Computer Science

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**Principal supervisor** Amariah Becker (2020-21), Thomas Weighill (2019–2020)

**Co-supervisor** Daryl DeFord (MIT 2018–2020), Rob Kropholler (2017–2020), Hao Liang (2013–2016)

### Selected Professional Service and Public-Facing Work

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#### Program committees and editorial boards

ACM Conference on Fairness, Accountability, and Computing (FAccT)	2022
Symposium on Foundations of Responsible Computing (FORC)	2021
Harvard Data Science Review	since 2019
Advances in Mathematics	2018–2023

#### Committee on Science Policy

American Mathematical Society	2020–2022
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#### Amicus Brief of Mathematicians, Law Professors, and Students

<i>principal co-authors: Guy-Uriel Charles and Moon Duchin</i>	2019
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Supreme Court of the United States, in *Rucho v. Common Cause* - cited in dissent

#### Expert work for redistricting litigation

<i>reports, deposition, and/or trial testimony</i>	2018—
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Wisconsin, North Carolina, Alabama, Pennsylvania, South Carolina, Texas, Georgia

*Johnson v. Wis. Elections Comm'n*, No. 2021AP1450-OA, 2022 WL 621082 (Wis. Mar. 3, 2022); *NC League of Conservation Voters, et al. v. Hall, et al.* No. 21-cv-500085 (Wake Cnty. Sup. Ct. 2021); *Milligan, et al. v. Merrill, et al.*, Case No. 2:21-cv-01530-AMM and *Thomas, et al. v. Merrill, et al.*, Case No. 2:21-cv-01531-AMM (N.D. Ala. 2021); *Carter v. Chapman*, No. 7 MM 2022, 2022 WL 702894 (Pa. Mar. 9, 2022); *SC NAACP et al. v. Alexander, et al.*, Case No. 3-21-cv-03302-MBS-TJH-RMG (D.S.C.) (three-judge ct.); *TX NAACP et al. v. Abbott*, Case No. 1:21-CV-00943-RP-JES-JVB. *Georgia State Conference of the NAACP et al. v. State of Georgia*, Case No. 1:21-CV-5338-ELB-SCJ-SDG.

#### Presenter on Public Mapping, Statistical Modeling

National Conference of State Legislatures	2019, 2020
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#### Committee on The Future of Voting: Accessible, Reliable, Verifiable Technology

National Academies of Science, Engineering, and Medicine	2017–2018
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#### Committee on the Human Rights of Mathematicians

American Mathematical Society	2016–2019
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