

No. 20220991-SC

IN THE SUPREME COURT
OF THE STATE OF UTAH

LEAGUE OF WOMEN VOTERS OF UTAH, ET AL.,
APPELLEES AND CROSS-APPELLANTS (PLAINTIFFS),

v.

UTAH STATE LEGISLATURE, ET AL.,
APPELLANTS AND CROSS-APPELLEES (DEFENDANTS)

**AMICUS BRIEF OF POLITICAL SCIENCE PROFESSORS
SUPPORTING APPELLEES AND CROSS-APPELLANTS AND AFFIRMANCE**

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STATEMENT OF INTEREST

Amici curiae are nationally recognized university research scholars and political scientists whose studies on electoral behavior, voter identity, and redistricting in the United States have been published in leading scholarly journals and books. *See infra* Appendix.

Amici have extensive professional knowledge and experience that will be relevant and helpful to the Court. They are among the leading scholars to study the predictability of voter behavior and the tools map-makers use to harness data relating to voter behavior and characteristics when preparing redistricting plans. *Amici* are well positioned to explain how gerrymandering affected this past decade's elections, including the 2018 midterms, and predict how recent developments in the capabilities of mapmaking software and data analysis tools have likely influenced the 2020 redistricting cycle and may influence cycles to come.

STATEMENT OF TIMELY NOTICE TO FILE BRIEF

Pursuant to Utah R. App. P. 25(a)(1), counsel for *Amici* provided timely notice to all counsel of record for all parties to this appeal of *Amici*'s intent to file this Brief.

STATEMENT OF CONSENT BY ALL PARTIES

Pursuant to Utah R. App. P. 25(e)(5), undersigned counsel for *Amici* hereby states that all parties to this appeal have consented under Utah R. App. P. 25(b)(2), to the filing of this Brief.

STATEMENT PURSUANT TO RULE 25(e)(6)

Pursuant to Utah R. App. P. 25(e)(6), counsel for *Amici* hereby states that no party or party's counsel authored this Brief in whole or in part; and no person, other than *Amici* and their counsel, contributed money that was intended to fund preparing or submitting this Brief.

ARGUMENT

I. PARTISAN GERRYMANDERS ARE NO LONGER SELF-LIMITING

A. Extreme Partisan Gerrymanders Deploying Advanced Technology Endure Despite “Wave” Elections

Before partisans had access to powerful computers, huge data sets, individual-level data, advanced software, and the latest social science, their gerrymandering efforts sometimes failed. Years ago, an overly ambitious gerrymander could fail to preserve legislative control for the line-drawing party if they misjudged the probable margin of victory or defeat in each district. *Davis*, 478 U.S. at 152 (O'Connor, J., concurring); *see also* Note, *Political Gerrymandering 2000-2008: “A Self-Limiting Enterprise”?*, 122 Harv. L. Rev. 1467, 1468–69 (2009) (evaluating partisan gerrymanders from 2000–2008). These relatively unsophisticated redistricting efforts have been labeled “dummymanders.” *See* Bernard Grofman & Thomas L. Brunell, *The Art of the Dummymander: The Impact of Recent Redistrictings on the Partisan Makeup of Southern House Seats*, in *Redistricting in the New Millennium* 183–84 (Peter Galderisi ed., 2005). But yesterday's dummymanders gave way to today's unerringly effective partisan gerrymanders.

After the 2010 and 2020 censuses, partisans used sophisticated technology and newly available data to redraw congressional and state legislative districts en masse. The 2011 maps displayed a sharp increase in partisan bias compared to the prior cycle’s maps, and remained unresponsive to voter preferences throughout the decade.¹ Anthony J. McGann et al., *Gerrymandering in America* 56–97 (2016). Despite some progress driven by state-level reforms in certain jurisdictions, the redistricting cycle following the 2020 Census likewise resulted in skewed maps. Michael C. Li et al., Brennan Ctr. for Justice, *Redistricting: A Mid-Cycle Assessment* 3–4 (2022).

Utah is a representative example. In 2018, congressional Democrats won the national popular vote by 8.6 percentage points over Republicans. See Harry Enten, *Latest House results confirm 2018 wasn’t a blue wave. It was a blue tsunami*, CNN Politics, Dec. 6, 2018, <https://cnn.it/2QxAHb5>. In that “wave” election, Democrats unexpectedly won Republican-leaning seats around Salt Lake City, only to lose them to Republicans in 2020. Li et al., *supra*, at 5. But in the latest redistricting cycle, Salt Lake City’s Democratic base was split across the state’s four congressional districts. *Id.* at n.3. Democrats lost any hope

¹ Responsiveness “measures the degree to which the makeup of a legislative chamber will change when voter preferences change.” Charles S. Bullock III, *Redistricting: The Most Political Activity in America* 110 (2010). When a map is responsive, a party wins more seats as it wins a larger share of votes. *Id.* Classic partisan redistricting techniques, such as packing or cracking voters of the opposing party, reduce responsiveness by ensuring that control of the district will not change, even if substantial numbers of voters change partisan preferences in an election year. *Id.* at 21.

of reclaiming those previously competitive seats—even in a “wave” election. *See id.* at App. 1. Experience in other states bear that out.

B. Courts and Independent Commissions, Not Voters, Overturned Some Extreme Partisan Gerrymanders

Despite disparities in relative control of the redistricting process between Republicans and Democrats,² voters identifying with both parties have seen their votes diluted in gerrymandered districts. Under many maps, despite significant fluctuations in party vote share since 2010, seat shares have not changed in over a decade. Recent exceptions like Michigan and Pennsylvania have something in common: There, gerrymandered lines were redrawn by courts or independent nonpartisan commissions.

Ohio. During the 2018 “wave” election, Democrats won only four of Ohio’s 16 congressional seats despite receiving 47.27% of the statewide congressional vote. *See* Cheryl L. Johnson, Clerk of the U.S. House of Representatives, *Statistics of the Congressional Election from Official Sources for the Election of November 6, 2018*, at 42 (2019) [hereinafter *2018 Election Statistics*], <https://bit.ly/3ObqQF7>. That is all the more striking because Democrats earned an approximately 6% greater vote share than they earned in the 2016 election, but only won the same four seats as in 2016. *See id.*; Karen L. Haas, Clerk of the U.S. House of Representatives, *Statistics of the Presidential and Congressional Elec-*

² In the 2021 cycle, Republicans control the drawing of 187 congressional districts while Democrats control only 75. Li et al., *supra*, at 5.

tion from *Official Sources for the Election of November 8, 2016*, at 60–61 (2017) [hereinafter *2016 Election Statistics*], <https://bit.ly/3WmGTBV>. The 2020 election saw the same outcome. See Cheryl L. Johnson, Clerk of the U.S. House of Representatives, *Statistics of the Congressional Election from Official Sources for the Election of November 3, 2020*, at 55–57 (2021) [hereinafter *2020 Election Statistics*], <https://bit.ly/3BstmiM>. Democrats won in the four districts packed with Democratic voters by 71%-to-29% in 2018 and 66%-to-33% in 2020. See *2018 Election Statistics, supra*, at 42; *2020 Election Statistics, supra*, at 56. Republicans cracked the remaining Democratic voters and won 12 seats by a combined 59%-to-40% in 2018 and by 63%-to-36% in 2020. *Id.* Ohio’s congressional gerrymander proved durable enough to absorb electoral shifts and preserve the seat share of the mapmakers’ preferred party.

In the 2021 redistricting cycle, the Ohio Supreme Court invalidated the new congressional map for violating the partisan-fairness requirement in Ohio’s Constitution. *Neiman v. LaRose*, 207 N.E.3d 607, 623 (Ohio 2022), *cert. petition pending*, No. 22-362 (Oct. 18, 2022). Nevertheless, the 2022 congressional elections used the biased map because the Republican-controlled Ohio Redistricting Commission passed new partisan-gerrymandered maps. See *What Redistricting Looks Like: Ohio*, FiveThirtyEight, <https://bit.ly/3W8IPOP> (last updated July 19, 2022).³ Democrats retained their four seats and gained a fifth, with a combined vote share of 61% to 39% in those five districts. See

³ Ohio lost one congressional seat through reapportionment following the 2020 Census.

Cheryl L. Johnson, Clerk of the U.S. House of Representatives, *Statistics of the Congressional Election from Official Sources for the Election of November 3, 2022*, at 39 (2023) [hereinafter *2022 Election Statistics*], <https://bit.ly/3pH5w04>.

Illinois. Between 2018 and 2022, Republicans held the same 5 out of Illinois’s 18 congressional districts despite receiving 39% and 41% of statewide congressional votes in the elections during that period, which translates to about 7 seats. *See 2018 Election Statistics, supra*, at 15; *2020 Election Statistics, supra*, at 24. In 2021, Democratic Governor J.B. Pritzker signed a new congressional map into law expected to give Democrats a 13-to-3 advantage with one highly competitive seat. *See What Redistricting Looks Like: Illinois*, FiveThirtyEight, <https://bit.ly/3pFcN0k> (last updated July 19, 2022).⁴ Indeed, in 2022, Republicans garnered 44% of the congressional vote but secured only 3 seats (18%). *See 2022 Election Statistics, supra*, at 16. Some commentators described Illinois’s as the most aggressive Democrat-drawn gerrymander in the nation because it “wastes”⁵ twice as many Republican votes as Democratic votes. *See Nathaniel Rakich & Tony Chow, Illinois May Be the Worst Democratic Gerrymander in the Country*, FiveThirtyEight (May 6, 2022), <https://bit.ly/42BoSSZ>.

Michigan. From 2010 through 2020, Michigan was among the most extreme gerrymanders. In 2018, Michigan Democrats won a majority of the State Senate vote share

⁴ Illinois lost one congressional seat through reapportionment following the 2020 Census.

⁵ Here, a vote qualifies as “wasted” either because it is cast in a district that is safely red or because it is vastly outnumbered by Democratic votes. *Id.*

but captured only 16 seats compared to 22 for Republicans. David A. Lieb, *Election Shows How Gerrymandering is Difficult to Overcome*, U.S. News & World Report (Nov. 17, 2018), <http://bit.ly/2BRSDVh>; Jonathan Oosting, *Why Democrats Won More Votes, But GOP Won More Legislative Seats in Michigan*, Detroit News (Nov. 20, 2018), <http://bit.ly/2GMEL2z>. In statewide races—unaffected by gerrymandering—Democratic candidates won the previously Republican-held offices of Governor, Secretary of State, and Attorney General, and Democratic Senator Debbie Stabenow was reelected. *See 2018 Michigan Election Results*, Mich. Dep’t of State (Nov. 26, 2018), <http://bit.ly/2018MichiganElections>. Yet, 2018 was the third straight election in which the gerrymandering party retained control of both state legislative chambers despite having near equal vote shares as its opponent. Tom Perkins, *Once Again, Michigan Dems Get More State Senate and House Votes, but GOP Keeps Power*, Detroit MetroTimes, Nov. 7, 2018, <https://bit.ly/42Zug2w>; *Quantifying the Level of Gerrymandering in Michigan*, Citizens Research Council of Mich. (June 2018), <http://bit.ly/2Nyzn3O>.

That changed in the 2021 redistricting cycle. Michigan created an independent commission to draw new maps, and the results showed some of the lowest partisan bias in the nation for this cycle. Li et al., *supra*, at 10; *see also* Samuel S.-H. Wang, *Michigan 2021 Commission Final Congressional Map (Chestnut)*, Princeton Gerrymandering Project (Nov. 5, 2021), <https://bit.ly/3M9VsnM>. The new map has almost equal shares of “wasted” votes for both parties, and almost 25% of districts are competitive. *See What Redistricting Looks Like: Michigan*, FiveThirtyEight, <https://bit.ly/45404nY> (last updated July 19,

2022). In the 2022 midterms, Democrats—who again won a majority of the vote—took control of both legislative chambers. See David A. Lieb, ‘*A Perfect Alignment*’: *Michigan Citizens Draw Fair Electoral Map*, *Cristian Sci. Monitor* (Nov. 22, 2022), <https://bit.ly/3MvphRm>.

Pennsylvania. After the 2010 Census, Republicans drew a gerrymandered congressional map. Democrats won only the same five seats out of 18 (27.7%) in 2012, 2014, and 2016—despite receiving 44.15% to 50.28% of the popular vote in those years. See Karen L. Haas, Clerk of the U.S. House of Representatives, *Statistics of the Congressional Election from Official Sources for the Election of November 6, 2012*, at 53 (2013), <https://bit.ly/3I7VaN9>; Karen L. Haas, Clerk of the U.S. House of Representatives, *Statistics of the Congressional Election from Official Sources for the Election of November 4, 2014*, at 41 (2015), <https://bit.ly/2DSMB8B>; *2016 Election Statistics* at 63–64.

In the 2018 election, the congressional map was invalidated under the State Constitution and replaced with a court-drawn map. Democrats received 55.5% of the two-party vote, and took nine of the State’s 18 districts. Samuel S.-H. Wang, *Pennsylvania 2018 Detailed Results*, Princeton Gerrymandering Project, <http://bit.ly/2BVrm4a> (click on Pennsylvania). Similarly, in the 2021 redistricting cycle, the Pennsylvania Supreme Court selected a map with one fewer Republican-leaning district than its predecessor. See *What Redistricting Looks Like: Pennsylvania*, FiveThirtyEight, <https://bit.ly/3MrRhoF> (last updated July 19, 2022). In 2022, using the new map, Democrats won the majority of seats

for the first time since 2008 with 47% of the statewide congressional vote. *2022 Election Statistics, supra*, at 42.

II. PARTISANS CAN EXPLOIT NEW TECHNOLOGY AND VOTER DATA TO CREATE MORE PRECISE AND DURABLE PARTISAN GERRYMANDERS THAN EVER BEFORE

Modern partisan gerrymanders resist demographic shifts and wave elections because of three modern phenomena. First, partisan affiliation (self-identification with a party) and voter behavior are highly stable and predictable, making voters' partisan affiliation a dependable trait on which map-makers can rely. Second, troves of newly available, granular voter data enables mapmakers to predict voter behavior with unprecedented accuracy. Third, advanced statistical and map-drawing applications enable partisans to translate voting data into districts that maximize partisan advantage. *See, e.g.*, Nick Corasaniti et al., *How Texas Plans to Make Its House Districts Even Redder*, N.Y. Times (Oct. 3, 2021), <https://nyti.ms/3IsNGoa> (illustrating how redistricting can be fine-tuned to neutralize demographic shifts).

A. Partisan Identity Is Highly Stable and Predictable

As a general matter, the partisan identity of voters is highly stable and mapmakers use partisan-identity data to predict voter behavior with a very high degree of confidence from election to election.⁶ Voter predictability enables gerrymanders to withstand wave

⁶ A panel survey funded by the National Science Foundation corroborates the high stability of partisan identity among voters. *See* Brian Schaffner & Stephen Ansolabehere, *2010–2014 Cooperative Congressional Election Study Panel Survey (Version 10)*, Harvard Dataverse (June 10, 2015), <http://bit.ly/2BUbeA5>.

elections, which are largely driven by differential turnout between voters identifying with each party. Daron Shaw, *If Everyone Votes Their Party, Why Do Presidential Election Outcomes Vary So Much?*, 10 *The Forum* 3 (2012).⁷

Social science research shows that voters are “socialized” into a particular party at an early age, and partisan affiliation tends to harden in early adulthood. See Donald P. Green, Bradley L. Palmquist & Eric Schickler, *Partisan Hearts and Minds* 6, 10-11 (2002). Once formed, these “identities are enduring features of citizens’ self-conceptions,” and “remain intact during peaks and lulls in party competition.” *Id.* at 4–5. Individuals’ partisan identification is, on average, more enduring and stable than their core values or positions on political issues. Paul Goren, *Party Identification and Core Political Values*, 49 *Am. J. Pol. Sci.* 882, 891–94 (2005); Thomas M. Carsey & Geoffrey C. Layman, *Changing Sides or Changing Minds: Party Identification and Policy Preferences in the American Electorate*, 50 *Am. J. Pol. Sci.* 464, 471–473 (2006); see also Alexander G. Theodoridis, *Me, Myself, and (I), (D), or (R)? Partisanship and Political Cognition Through the Lens of Implicit Identity*, 79 *J. Pol.* 1253 (Oct. 2017).

⁷ In 2018, registered Democrats and Democratic-leaning independents—including groups that often skip midterms, such as youth voters—showed up to the polls in significantly higher numbers than Republicans. Dan Keating & Kate Rabinowitz, *Turnout Was High for a Midterm and Even Rivalled a Presidential Election*, *Wash. Post*, Nov. 8, 2018, <https://wapo.st/2U6Gzq4>; Abby Vesoulis, *The 2018 Elections Saw Record Midterm Turnout*, *Time Magazine*, Nov. 12, 2018, <https://bit.ly/3OzqnfY>. And in the 2020 presidential election—which saw the highest turnout in 120 years of elections—an estimated 50% of voters identified or leaned Democrat while 48% identified or leaned Republican. Pew Research Ctr., *Behind Biden’s 2020 Victory* 24 (Jun. 30, 2021), <https://pewrsr.ch/4535IMW>.

Partisan attachment is a stronger predictor of voting behavior than gender, class, religion, and often race. Green, *Partisan Hearts and Minds*, *supra*, at 3; *see also* Stephen Ansolabehere & Bernard L. Fraga, *Do Americans Prefer Coethnic Representation? The Impact of Race on House Incumbent Evaluations*, 68 *Stan. L. Rev.* 1553, 1589 (2016). Thus, the distribution of partisan identities among the electorate “provides powerful clues as to how elections will be decided.” Donald P. Green, Bradley L. Palmquist & Eric Schickler, *Partisan Stability: Evidence from Aggregate Data*, in *Controversies in Voting Behavior* 356, 356 (Richard G. Niemi & Herbert F. Weisberg eds., 4th ed. 2001).

In recent years, the predictive power of partisan identity has only increased. Joseph Bafumi & Robert Y. Shapiro, *A New Partisan Voter*, 71 *J. Pol.* 1, 3 (2009). Based on an analysis of American National Election Studies time-series data conducted in 2015, the “observed rate of Americans voting for a different party across successive presidential elections has never been lower,” indicating that each party has a reliable and predictable “base of party support that is less responsive to short-term forces.” Corwin D. Smidt, *Polarization and the Decline of the American Floating Voter*, 61 *Am. J. Pol. Sci.* 365, 365, 379–81 (2017). A Pew Research Report notes that “[t]oday, 92% of Republicans are to the right of the median Democrat, and 94% of Democrats are to the left of the median Republican.” Pew Research Ctr., *Political Polarization in the American Public* 6 (June 12, 2014), <https://pewrsr.ch/2Exx0v4>.

Political scientists also have detected an increase in the *intensity* of party preferences within the electorate. Empirical evidence shows that “[o]rdinary Americans increasingly

dislike and distrust those from the other party.” Shanto Iyengar et al., *The Origins and Consequences of Affective Polarization in the United States*, 22 *Ann. Rev. Pol. Sci.* 129, 130 (2019); see also Alan I. Abramowitz & Steven Webster, *The Rise of Negative Partisanship and the Nationalization of U.S. Elections in the 21st Century*, 41 *Electoral Stud.* 12 (2016); Pew Research Ctr., *As Partisan Hostility Grows, Signs of Frustration with the Two-Party System* 12–13 (2022), <https://pewrsr.ch/3MAPdLr>.

Today’s partisans are less willing “to treat the actions of partisan opponents as legitimate,” and today’s partisan identification “is all encompassing and affects behavior in both political and nonpolitical contexts.” Shanto Iyengar & Sean J. Westwood, *Fear and Loathing Across Party Lines: New Evidence on Group Polarization*, 59 *Am. J. Pol. Sci.* 690, 705 (2015); see also Lilliana Mason, *Uncivil Agreement* (2018); Alexander G. Theodoridis et al., *Separated by Politics? Disentangling the Dimensions of Discrimination*, *Pol. Behavior* (2022), <https://bit.ly/41T8Na3>. Independent voters are not immune to the effects of partisan intensity, given that “[m]ost of those who identify as independents lean toward a party.” Pew Research Ctr., *A Deep Dive into Party Affiliation* 4 (2015), <https://pewrsr.ch/2Exh4ci>. Voters who identify as independents but lean towards a party generally exhibit policy opinions and voting behavior similar to outright partisans. David B. Magleby & Candice Nelson, *Independent Leaners as Policy Partisans: An Examination of Party Identification and Policy Views*, 10 *The Forum* 1, 17 (2012). Independents who lean to one party or another “are far more likely to cite negative than positive factors for why they form their loose partisan ties”—that is, they are likely to lean Democratic or

Republican because they view the other party's policies as harmful to the country. *See* Pew Research Ctr., *Partisanship and Political Animosity in 2016*, at 6 (2016), <https://pewrsr.ch/2NtK2MV>; *see also* Pew Research Ctr., *Partisan Hostility*, *supra*, at 38–41.

One metric that coincides with increased and stable partisanship is the decline in split-ticket voting.⁸ While split-ticket voting was common in the 1970s and 1980s, the 2012 election featured record-high numbers of straight-ticket voting—that is, voting for the candidate for President from one party and voting for Congress members from the same party. *See* Abramowitz & Webster, *supra*, at 12, 13. The straight-ticket voting rate in the 2012 presidential and House elections was approximately 89%, up from 70% in 1972. *Id.* at 13. In terms of shared variance, the resulting relationship between 2012 presidential and House election outcomes was three times stronger than in the 1970s. *Id.* at 18. The 2012 rate of straight-ticket voting in the presidential and Senate elections was approximately 90%, resulting in a relationship between presidential and Senate election outcomes that was similarly much stronger than in the 1970s. *Id.* at 13, 19. Nationalized, party-line voting behavior also influences elections for prominent state offices (such as governorships), although split-ticket voting remains common in other state and local elections. *See*

⁸ Split-ticket voting refers to the phenomenon of a voter opting for the candidate from one party in the presidential election and the candidate of another party in the House or Senate elections.

generally Daniel J. Hopkins, *The Increasingly United States: How and Why American Political Behavior Nationalized* (University of Chicago Press 2018); Shiro Kuriwaki, *Ticket Splitting in a Nationalized Era* (Mar. 2023) (manuscript at 1, 29).

Declines in split-ticket voting also coincide with declines in split *outcomes* (i.e., congressional districts carried by a presidential candidate from one party, but won by a House candidate of the opposite party).⁹ In 2020, only 16 districts elected a House member from a different party than their preferred presidential candidate, and only one district (Maine) saw a split outcome between the Senate and presidential races. See Philip Bump, *2020 Saw the Least Split-Ticket House Voting in Decades*, Wash. Post (Feb. 19, 2021), <https://wapo.st/3pA91Fr>; Nathaniel Rakich & Ryan Best, *There Wasn't That Much Split-Ticket Voting in 2020*, FiveThirtyEight (Dec. 2, 2020), <https://bit.ly/3O3Ho1Q>.¹⁰ Previously, 2016 marked the first election since 1914—when the country began electing Senators by popular vote—in which no State had divided outcomes between Senate and presidential votes. Harry Enten, *There Were No Purple* States on Tuesday*, FiveThirtyEight (Nov. 10, 2016), <https://53eig.ht/2XoDDHk>. To be sure, midterm elections have exhibited

⁹ Split outcomes between governor and Senate votes are slightly more common in midterm elections. See J. Miles Coleman, *2022's Split Ticket States*, Univ. of Va. Ctr. For Politics: Sabato's Crystal Ball (Nov. 30, 2022, <https://bit.ly/3O9UyKM>).

¹⁰ Due to the sharp decline of split-ticket voting, knowledge of top-ticket voting is becoming an increasingly useful proxy when assessing how people will vote in a legislative race, further enhancing the reliability of predictive voting models, discussed *infra* at Section II.B.

more divided outcomes between governor and Senate votes including in influential battlegrounds states, but that may change as gubernatorial elections become more nationalized. *See, e.g.,* Geoffrey Skelley, *Few Midterm Voters Backed Different Parties for Senate and Governor*, FiveThirtyEight (Nov. 28. 2022), <https://bit.ly/3WIBNpR> (split outcomes in 1-in-6 to 1-in-4 states going back to 2010).

Together, stable partisan identity, intensifying partisanship, and declining ticket-splitting allow mapmakers to rely on the predictability of voter behavior as never before when maximizing the partisan bias and durability of gerrymanders.

B. Voter Data Enables Partisans to Predict Voting Behavior at a Granular Level

Today’s mapmakers have access to more voter data about partisan affiliation than they did just a few years ago. Data gathering has become so precise that voters can be individually targeted with customized messages. *See* Dan Patterson, *How Campaigns Use Big Data Tools to Micro-Target Voters*, CBS News (Nov. 6, 2018), <https://cbsn.ws/2BTWKjp>. Data brokers advertise their ability to create a “scientific understanding of the voter” to calculate the “likelihood for a certain behavior of a voter based on multiple characteristics like income, age, and geography.” Civis Analytics, *Political Campaign Tools—Running a Digital Campaign* 12 (2018), <http://bit.ly/2SoTWjX>.

Data brokers are experienced in creating “augmented voter files,” or extensive public and commercial datasets of voter data. *See* Eitan D. Hersh, *Hacking the Electorate: How Campaigns Perceive Voters* 67, 69–72 (2015). These voter files combine traditional voter registration records with substantial information, such as “data from frequent-buyer

cards at supermarkets and pharmacies, hunting- and fishing-license registries, catalog- and magazine-subscription lists, membership rolls from unions, professional associations, and advocacy groups.” Chris Evans, *It’s the Autonomy, Stupid: Political Data-Mining and Voter Privacy in the Information Age*, 13 Minn. J.L. Sci. & Tech. 867, 883 (2012).

The 2018 elections demonstrated the utility of voter records, data, social media and even credit reports to micro-target and track voters. Patterson, *supra*. The 2018 election stood out for its unprecedented use of social media information to predict and influence voter behavior. Scott Shane & Sheera Frenkel, *Russian 2016 Influence Operation Targeted African-Americans on Social Media*, N.Y. Times (Dec. 17, 2018), <https://nyti.ms/2SsqliR>. During the 2018 Georgia governor’s race, for example, candidate Stacey Abrams eschewed traditional, broad targeting tactics, instead targeting an “untapped market” of 90,000 “irregular” voters her campaign identified as “persuadable” based on collected data. Bill Barrow, *Inside Stacey Abrams’ Strategy To Mobilize Georgia Voters*, AP News (Oct. 12, 2018), <http://bit.ly/2NqsIbN>. Since 2020, digital consultants have broadcast tailored political ads via video streaming services to reach carefully selected groups of voters, with such ads accounting for up to 15% of the projected ad spending for 2022 elections. Natasha Singer, *This Ad’s for You (Not Your Neighbor)*, N.Y. Times (Sept. 20, 2022), <https://nyti.ms/3IbUxIP>.

The quantity and granularity of publicly available voter data, and improvements in data analytics, will allow mapmakers to assess and predict partisan affiliation at both the individual and aggregate levels more accurately than ever. Data broker Civis Analytics

correctly forecasted the winner in 383 out of 394 contested races (97%) in 2018 and its estimate of the national popular vote was accurate to within tenths of a percent. *Data science and the Midterm Elections: Breaking Down the Results*, Civis Analytics, (Dec. 5, 2019), <http://bit.ly/2XpRLjB>. By inputting proprietary voter data and existing Census and consumer data into advanced statistical models and predictive analytics, political campaigns can determine partisan affiliation at a level of precision that was unachievable in even the recent past.

C. Advanced Analytics and Statistical Techniques Enable Partisans to Maximize Partisan Advantage in Drawing Districts

Advanced analytics and new statistical techniques allow mapmakers to create durable gerrymanders. James Manyika et al., *Big Data: The Next Frontier for Innovation, Competition, and Productivity*, McKinsey Global Institute (June 2011), <https://mck.co/2VhvlPC>. Legislators are “now more knowledgeable about the need to avoid drawing a *dummymander* . . . than they were in past decades,” and mapmakers have “gained more technical sophistication in mapping historical election data into proposed districts, and then checking to make sure that they do not make a *dummymandering* kind of mistake.” Bernard Grofman & Jonathan R. Cervas, *Can State Courts Cure Partisan Gerrymandering: Lessons from League of Women Voters v. Commonwealth of Pennsylvania (2018)*, 17 Election L. J. 264, 278 (2018), <http://bit.ly/2BTrnpj>.

During the 2010 redistricting cycle, mapmakers had access not only to expansive data sets that allowed them to predict voter behavior accurately, but to new and/or improved redistricting software, such as AutoBound, developed by Citygate GIS; Maptitude,

developed by Caliper Corporation; and ArcGIS, developed by ESRI. This type of software, combined with modern statistical techniques, allowed mapmakers to draw durably biased maps. Users could quickly and easily develop redistricting plans based on customizable data sets, including data that predict the projected partisan affiliation of voters. *See, e.g.*, AutoBound Redistricting Software, Citygate GIS, <http://bit.ly/2TnXxU0> (last visited May 19, 2023).

Mapmakers aligned with both Republicans and Democrats used these techniques and technologies to design maps in the two most recent redistricting cycles. For example, in North Carolina’s 2011 redistricting process, Maptitude was used to collect past election data and to “pursue partisan advantage without sacrificing compliance with traditional districting criteria.” *See Common Cause v. Rucho*, 318 F. Supp. 3d 777, 883 (M.D.N.C. 2018) (quoting *Whitford v. Gill*, 218 F. Supp. 3d 837, 889 (W.D. Wis. 2016)). North Carolina’s 2011 maps had substantial and durable partisan bias and preserved the Republican Party’s 10-3 advantage in North Carolina’s congressional delegation, despite a 0.7-to-1 ratio of registered Republicans to Democrats in 2012. *See id.* at 869; Royden, Li & Rudensky, *supra*, at 1, 6, 25 (2018); *Voter Registration Statistics*, N.C. St. Board Elections & Ethics Enforcement, <http://bit.ly/2TkJ0rZ> (last visited May 19, 2023).

Similarly, in Maryland, the Democratic Party leadership retained a consultant who used Maptitude to simulate hypothetical districts and election results using granular voter data. *Benisek v. Lamone*, 348 F. Supp. 3d 493, 502–03 (D. Md. 2018). Under the maps

that emerged from that process, Democrats won seven of Maryland’s eight congressional districts in 2012, capturing a historically safe Republican seat by 21 points. *Id.* at 501–02.

While historical mapmakers may have experimented by drafting three or four maps, now they can use software to generate tens of thousands of possibilities, all precisely engineered based on hyper-local voting data, allowing partisan actors to select the single map that exhibits the greatest partisan advantage. These tools enable mapmakers to reduce the risk that they have drawn anything less than a maximally partisan map, which in turn enable them to create more durable and aggressive partisan gerrymanders.

III. WITHOUT JUDICIAL INTERVENTION, PARTISAN GERRYMANDERS WILL ONLY BECOME MORE DURABLE AND RESISTANT TO WAVE ELECTIONS

As powerful as current methods are, predictive modeling and other large-scale analytical tools will become more potent in the near future. New technologies and data sources, such as augmented voter files and modern machine-learning algorithms, will make it easier for mapmakers to predict Americans’ decision-making habits in a more nuanced and accurate way than ever before. New data analysis techniques will enable partisan mapmakers to create gerrymanders that are even more biased, more durable, and more capable of withstanding the effects of “wave” election years.

A. Partisan Operatives Will Deploy Even More Advanced Data Analytics to Dilute the Votes of Opposition Party Voters

Data analytics have grown more potent due to two important developments: (1) greater commercial availability of compiled data about Americans, and (2) more powerful

and precise data analysis techniques. Like their corporate counterparts, political parties are leveraging these advancements.

First, political data brokers are growing increasingly sophisticated in their ability to collect public voter information and create augmented voter files. *See supra* Section II.B.; David W. Nickerson & Todd Rogers, *Political Campaigns and Big Data*, 28 J. Econ. Persp. 51 (2014). These augmented files have emerged only recently in part because large-scale, public voter information was not available until the mid-2000s. *See* Hersh, *supra*, at 67. Candidates in 2024 will be able to target their campaign efforts and micro-targeted campaign appeals to the same voters and using the same data and the same prediction of their behavior as their party did in drawing the new district lines for that election.

In future redistricting cycles, augmented voter files will be powerful mapmaking tools allowing mapmakers to predict voting patterns at an individualized level. For example, private vendors can predict a voter's race with reasonable accuracy by using the voter's name and the general racial composition of their neighborhood. *Id.* at 127. Such accurate, individualized data will only enhance mapmakers' abilities to create district maps with extreme partisan bias.

Second, political vendors can deploy data-analysis techniques involving machine learning, allowing them to recognize previously undiscovered individual voting patterns. *See supra* Section II.A. "Machine learning" refers to the ability of a computer to learn from a data set without relying only on a set of pre-existing rules. *See* Cary Coglianese &

David Lehr, *Regulating by Robot: Administrative Decision Making in the Machine-Learning Era*, 105 Geo. L.J. 1147, 1156-57 (2017). Modern machine-learning algorithms outperform traditional methods in predictive accuracy because the algorithms are able to apply numerous variables to large volumes of data and make inferences about the behavior of individuals. *See id.* In addition, the algorithm can determine by itself which variables are relevant for predictive purposes, whereas traditional statistical techniques only allowed scientific researchers to make predictions by designing models based on rigid, pre-defined assumptions. *See id.*

In past campaigns and redistricting efforts, a political party may not have used anything more than basic regression techniques to predict voter behavior. *See* Nickerson & Rogers, *supra*, at 59. However, such techniques are of limited utility when confronted with complicated relationships involving a large number of variables. *See id.* at 59-60. Additionally, in the context of voter behavior, relationships between variables are often nonlinear and context-dependent. *Id.* at 59–61. For example, older voters tend to turn out at a higher rate than younger ones, but this relationship peaks between ages 60 and 70, and for voters older than 70, the turnout gap compared to younger voters begins to narrow. *Id.* at 61. Because of such nuances, past campaigns had difficulty predicting individual voter behavior with accuracy. *See id.* at 59–61.

Modern machine-learning algorithms, however, do not suffer from these drawbacks. Machine-learning algorithms are better able to process nonlinear nuances within a voting model, such as the above-mentioned relationship between voting and age, and can do so

with less reliance on the skill of any particular analyst. *See id.*; Olivia Guest, Frank J. Kanayet, and Bradley C. Love, *Gerrymandering and Computational Redistricting*, 2 J. Computational Soc. Sci. 119, 121, 128 – 129 (Dec. 12, 2018), <http://bit.ly/2TlmXBm>.

B. “Matched-Slice” Gerrymandering Designed to Maximize Partisan Bias Will Soon Be Possible

The availability of augmented voter files and analytical tools will soon enable map-makers to create gerrymanders far more biased and durable than before—including even those drawn since the 2011 redistricting cycle.

A theoretical technique called “matched-slice” gerrymandering can draw maps that maximize partisan bias based on accurate, individualized knowledge of voter behavior. See Christopher S. Elmendorf, *From Educational Adequacy to Representational Adequacy: A New Template for Legal Attacks on Partisan Gerrymanders*, 59 William & Mary L. Rev. 1601, 1650–51 (2018) (citing John N. Friedman & Richard T. Holden, *Optimal Gerrymandering: Sometimes Pack, but Never Crack*, 98 Am. Econ. Rev. 113, 126, 134–35 (2008)). In a matched-slice gerrymander, a district is divided optimally from the map-makers’ perspective if each geographic subdivision within the district contains matched-slice representations—*i.e.*, highly partisan Republican voters are paired with highly partisan Democratic voters, center-right Republicans are paired with center-left Democrats, and so on.

Matched-slicing strategies are optimal because they neutralize a party’s most reliable voters. For example, if a group of reliable Republican voters resides in one area, a gerrymander could dilute their power by drawing a map such that the strong Republican

base is split up, with each “slice” of strong Republicans being matched with a slightly larger and equally fervent group of reliable Democratic voters. Over time, this “matched-slice” strategy will produce optimal partisan results because it most efficiently distributes a party’s base of reliable voters. *See* Friedman & Holden, *Optimal Gerrymandering*, 98 *Am. Econ. Rev.* at 126; *see also* Adam B. Cox & Richard T. Holden, *Reconsidering Racial and Partisan Gerrymandering*, 78 *U. Chi. L. Rev.* 553, 567 (2011).

Historically, partisan redistricting efforts lacked sufficient individualized voter data and the ability to process that data for use in matched-slice strategies. *See* Elmendorf, *supra*, at 1650–51. Instead, mapmakers relied on broader, geographic-based proxies, such as ward-level data of voter preferences. *See id.*¹¹ With the proliferation of individualized voter data, however, future mapmakers using new techniques such as the matched-slice strategy will be increasingly capable of forming districts designed to entrench and expand partisan bias to withstand “wave” election years with even higher vote differentials than 2018.

¹¹ For example, a district may contain a simple 52% majority of voters siding with the party in control of the mapmaking process, but that majority may be composed of a mix of strong partisan voters and more moderate voters. This distribution is far less reliable than an “ideal” district containing a 52% majority of only strong partisan voters because the former, “mixed” district is subject to swing voters. *See* Cox & Holden, *supra*, at 567. Historically, it was not possible to ensure this distribution reliably because of difficulty in obtaining sufficiently robust and precise individual-voter data. *See* Nickerson & Rogers, *supra*, at 55–56. Instead, to combat this distribution, historical mapmakers would have to either accept the risk of swing voters or inefficiently move more partisan voters into districts to ensure that the district votes for the mapmaker’s party. *See* Cox & Holden, *supra*, at 565–67.

IV. SOCIAL SCIENCE PROVIDES OBJECTIVE AND RELIABLE TOOLS THAT COURTS COULD USE TO EVALUATE PARTISAN BIAS IN MAPS

Even as data and technology have been used to create maps with extreme and durable partisan bias, these same tools have been and can continue to be a part of the solution to extreme partisan gerrymandering. With the aid of expert witnesses, courts can use advanced computer-modeling techniques to identify partisan gerrymanders.

For example, modern software and computers can randomly generate a large number of alternative redistricting plans that adhere to traditional redistricting criteria and then compare the computer-generated alternatives to existing plan. If the existing plan is more biased than all or almost all of the plans the computer has drawn, courts could conclude that traditional criteria do not explain the plan. *See* Daniel B. Magleby & Daniel Mosesson, *A New Approach for Developing Neutral Redistricting Plans*, 26 *Pol. Analysis* 147–67 (2018); Jowei Chen & David Cottrell, *Evaluating Partisan Gains from Congressional Gerrymandering: Using Computer Simulations to Estimate the Effect of Gerrymandering in the U.S. House*, 44 *Electoral Stud.* 329, 331, 332 (2016); Wendy K. Tam Cho & Yan Y. Liu, *Toward a Talismanic Redistricting Tool: A Computational Method for Identifying Extreme Redistricting Plans*, 15 *Election L.J.* 351, 353 (2016). In recent years, courts have utilized such innovative, large-scale analytical tools to assess partisan bias in maps. *See, e.g., League of Women Voters of Mich. v. Johnson*, No. 2:17-cv-14148, 2018 WL 6257476, at *7–9 (E.D. Mich. Nov. 30, 2018), *rev'd on other grounds*, 2018 WL 10096237 (6th Cir. 2018); *Raleigh Wake Citizens Ass'n v. Wake Cty. Bd. of Elections*, 827 F.3d 333, 344–45 (4th Cir. 2016); *City of Greensboro v. Guilford Cty. Bd. of Elections*, 251 F. Supp. 3d 935,

949 (M.D.N.C. 2017). And indeed, state courts have tackled partisan gerrymandering since the *Rucho* majority highlighted their unique ability to do so. *See, e.g., Adams v. Dewine*, 195 N.E.3d 74 (Ohio 2022); *Harkenrider v. Hochul*, 197 N.E.3d 437 (N.Y. 2022); *Szeliga v. Lamone*, No. 02-cv-21-001816 (Md. App. Ct. Mar. 25, 2022), *appeal dismissed*, 478 Md. 241 (Apr. 4, 2022); *In re 2021 Redistricting Cases*, No. S-18332, 2023 WL 3030096 (Alaska Sup. Ct. Apr. 21, 2023).

A variant of these modeling techniques is the Markov Chain Monte Carlo algorithm, which involves making a large number of small and randomized adjustments to an existing map. *See generally* Maria Chikina, Alan Frieze & Wesley Pegden, *Assessing Significance in a Markov Chain Without Mixing*, 114 Proc. Nat'l Acad. Sci. 2860 (2017); Benjamin Fifield et al., *Automated Redistricting Simulation Using Markov Chain Monte Carlo*, 29 J. Computational & Graphical Stat. 715 (2020); Daryl DeFord et al., *Recombination: A Family of Markov Chains for Redistricting*, 3 Harv. Data Sci. Rev. 1 (2021); Eric A. Autry et al., *Metropolized Multiscale Forest Recombination for Redistricting*, 19 Multiscale Modeling & Simulation 1885 (Jan. 2021). Another variant, the Sequential Monte Carlo algorithm, generates large numbers of maps in parallel by drawing districts at random starting from a blank map and testing the resulting maps against constraints (including traditional redistricting principles). *See* Cory McCartan & Kosuke Imai, *Sequential Monte Carlo for Sampling Balanced and Compact Redistricting Plans*, *Annals Applied Stat.* (forthcoming) (manuscript at 1–2), <https://arxiv.org/pdf/2008.06131.pdf>. Under these techniques, if the vast majority of simulated maps exhibit a reduction in partisan bias when compared to the

real-world map, that can support a conclusion that the real-world map is a partisan gerrymander.

Courts and litigants can use computer modeling techniques and social science tools to identify gerrymanders and evaluate proposed remedial election plans. These tools have been vetted by scholars and political scientists and are generally regarded as objective, verifiable, and reliable mechanisms to assess partisan bias. This Court should set a standard allowing lower courts to use the tools now available to identify constitutional violations.

CONCLUSION

For the foregoing reasons, *Amici* respectfully request that the Court affirm the judgment below and remand for expedited trial as requested by Appellees and Cross-Appellants.

Respectfully submitted,

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CERTIFICATE OF COMPLIANCE

I hereby certify that:

1. This brief complies with the word limits set forth in Utah R. App. P. 25(f) because this brief contains 6190 words, excluding the parts of the brief exempted by Utah R. App. P. 25(f). This brief uses Times New Roman 13-point font.

2. This brief complies with Utah R. App. P. 21(h) regarding public and non-public filings.

DATED this 19th day of May, 2023.

/s/ J. Tayler Fox

J. TAYLER FOX

CERTIFICATE OF SERVICE

I hereby certify that on the 19th day of May, 2023, I caused the foregoing to be served

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APPENDIX

LIST OF *AMICI CURIAE*

Professor Alexander G. Theodoridis is an assistant professor of political science at the University of Massachusetts Amherst.

Professor Andrew Gelman is Higgins Professor of Statistics and a professor of political science and the Director of the Applied Statistics Center at Columbia University.

Professor Ariel White is Silverman (1968) Family Career Development Associate Professor of Political Science at MIT.

Professor Barry Burden is a professor of political science and the Lyons Family Chair in Elector Politics at the University of Wisconsin-Madison.

Professor Brian F. Schaffner is Newhouse Professor of Civic Studies at Tufts University.

Professor David C. Kimball is a professor of political science at the University of Missouri-St. Louis.

Professor David Canon is a professor of political science at the University of Wisconsin-Madison.

Professor David W. Rhode is Ernestine Friedl Distinguished Professor Emeritus of Political Science and Director of the Political Institutions and Public Choice Program at Duke University.

Professor Donald P. Green is a professor of political science at Columbia University.

Professor Eric Schickler is Jeffrey & Ashley McDermott Professor of Political Science at the University of California, Berkeley.

Professor J. Morgan Kousser is a professor of history and social science at California Institute of Technology.

Professor Kosuke Imai is a professor of government and statistics at Harvard University.

Professor Logan M. Dancey is an associate professor of government at Wesleyan University.

Professor Marie Hojnacki is an associate professor of political science and Associate Head and Director of World Campus Programs of the department of political science at Penn State University.

Professor Michael H. Crespin is a professor of political science and Director and Curator of the Carl Albert Congressional Research and Studies Center at the University of Oklahoma.

Professor Neil Malhotra is the Edith M. Cornell Professor of Political Economy and Louise and Claude N. Rosenberg, Jr. Director of the Center for Social Innovation at Stanford Graduate School of Business and (by courtesy) professor of political science at Stanford School of Humanities and Sciences.

Professor Paul Goren is a professor of political science and the Chair of the department of political science at the University of Minnesota.

Professor Ryan Vander Wielen is associate professor of political science at Stony Brook University.