

Nos. 18-422, 18-726

**In The
Supreme Court of the United States**

—◆—
ROBERT A. RUCHO, et al.,
Appellants,

v.

COMMON CAUSE, et al.,
Appellees.

—◆—
**On Appeal From The United States District Court
For The Middle District Of North Carolina**

—◆—
LINDA H. LAMONE, et al.,
Appellants,

v.

O. JOHN BENISEK, et al.,
Appellees.

—◆—
**On Appeal From The United States District Court
For The District Of Maryland**

—◆—
**BRIEF OF *AMICI CURIAE*
POLITICAL SCIENCE PROFESSORS
IN SUPPORT OF APPELLEES AND AFFIRMANCE**

—◆—
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STATEMENT OF INTEREST¹

Amici curiae are all 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 at 1a.

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 mapmakers use to harness data relating to voter behavior and characteristics when preparing redistricting plans. *Amici* are well positioned to explain how gerrymandering affected this decade's elections, including the 2018 midterms, and predict how recent developments in the capabilities of mapmaking software and data analysis tools are likely to influence the 2020 redistricting cycle and beyond.

**SUMMARY OF ARGUMENT**

In 1986, Justice O'Connor observed that "political gerrymandering is a self-limiting enterprise" because

¹ No counsel for any party authored this brief in whole or in part. No person other than *Amici* and their counsel made a monetary contribution intended to fund the preparation or submission of this brief. Pietro Signoracci, Michael Pernick, Amitav Chakraborty, and Brittney Xu of Paul, Weiss, Rifkind, Wharton, and Garrison LLP contributed to the preparation of this brief. The parties have filed blanket consents.

a “swing in overall voting strength will tend to cost the legislative majority more and more seats as the gerrymander becomes more ambitious.” *Davis v. Bandemer*, 478 U.S. 109, 152 (1986) (O’Connor, J., concurring). In other words, Justice O’Connor assumed that a “wave” election—an election in which one party wins the popular vote share by a significant margin over the other—would remedy partisan gerrymanders without judicial intervention. “There is no proof before us,” Justice O’Connor observed, “that political gerrymandering is an evil that cannot be checked or cured by the people or by the parties themselves.” *Id.*

When Justice O’Connor made this observation, Pac-Man was still a popular video game. Microsoft had just released its first Windows operating system. Bill Gates and Steve Jobs were unknown to the general public. And politicians did not have the sophisticated software, processing power, or data to exploit voter behavior that they have today. They lacked the tools to create durable partisan gerrymanders—one in which the gerrymandering party retains maximal control of the legislature for multiple election cycles spanning the entire decennial period following its implementation of the gerrymander.

The tools have arrived. Partisans are using exponentially greater computing power, sophisticated data analytics and data sets, and social science to create maps that are incompatible with democracy. Nevertheless, appellants urge this Court to repose its faith in “politically accountable” state legislatures. *Rucho v. Common Cause*, Appellants’ Br. at 2, 21, 34, 36. Their

argument assumes that sooner or later a swing in the popular vote will produce a legislature that is accountable to the people. *Amici* here urge the Court to reject that assumption. Even if it were correct in the past, it is unwarranted today and for the foreseeable future. Today's partisan gerrymanders are technologically-designed to survive swings in the popular vote. As a result, voters in gerrymandered districts cannot cure them.

The 2018 midterm election results provide powerful new evidence demonstrating that modern partisan gerrymanders are durable and, as a result, state legislatures are not politically accountable. Significant swings in the popular vote in 2018 did not lead to electoral change in States with partisan gerrymanders, demonstrating a lack of responsiveness to voter preferences. Notwithstanding a significant surge in popular support—nationwide and in many States with gerrymandered maps—Democratic candidates were generally unable to gain seats in congressional and state legislative chambers with Republican gerrymanders. Similarly, in recent election cycles, Democratic gerrymanders were able to resist voter preferences for Republican candidates. Voters in gerrymandered districts need this Court's intervention to vindicate their constitutional rights. They cannot do so by voting when a state legislature has drawn their district to dilute their vote and render it ineffective.

Mapmakers today are able to devise gerrymanders that withstand partisan waves as a result of an explosion in granular voter data—now widely

available—that allow mapmakers to predict partisan behavior with a high degree of accuracy, coupled with advancements in map-drawing software that allow mapmakers to entrench maximal partisan bias.² As a result of these technological advances, modern gerrymanders are able to withstand wave elections such as the 2018 midterms, and gerrymandering techniques that were only theoretical in the 2010 redistricting cycle will become commonplace in the 2020 redistricting cycle and beyond.

Courts can and should provide redress for injuries caused by partisan gerrymandering. The same tools that enable politicians and their consultants to draw such precise and durable maps also enable courts to determine whether a partisan gerrymander is unconstitutional. Just as social science and technology have facilitated and will facilitate partisan gerrymandering, those same fields provide tools that can be used to identify and remedy such gerrymandering when it occurs.



² An electoral map exhibits partisan bias or partisan asymmetry when one party wins a larger number of legislative seats with $x\%$ of votes that the other party would win if it had received the same percentage of votes under the same map. See Jonathan N. Katz, Gary King, & Elizabeth Rosenblatt, *Theoretical Foundations and Empirical Evaluations of Partisan Fairness in District-Based Democracies*, Dec. 2, 2018 (working paper), <http://j.mp/2BkgYTP>; Andrew Gelman & Gary King, *A unified model for evaluating electoral systems and redistricting plans*, 38 *Am. J. of Pol. Sci.* 514-54 (1994).

ARGUMENT

I. EVIDENCE FROM THE 2018 ELECTIONS SHOWS THAT PARTISAN GERRYMANDERS ARE NO LONGER SELF-LIMITING

Before partisans had access to powerful computers, huge data sets, individual-level data, advanced software, and the latest social science, their gerrymandering efforts were sometimes prone to failure. In past years, an overly-ambitious gerrymander could fail to preserve legislative control for the majority line-drawing party if it 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 for years 2000-2008). These relatively unsophisticated redistricting efforts may be labeled as "dummymanders" today. *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 have given way to today's unerringly effective partisan gerrymanders.

After the 2010 Census, partisans used sophisticated technology and newly-available data to redraw congressional and state legislative districts en masse. As a whole, the new maps displayed a sharp increase in partisan bias when compared to the prior cycle's maps, and have been unresponsive to voter preferences

throughout the course of the decade.³ Anthony J. McGann et al., *Gerrymandering in America* 56-97 (2016). *Amici* made this observation to the Court last term, and the 2018 results confirm their analysis. See Brief for Political Science Professors as *Amici Curiae*, *Gill v. Whitford*, 138 S. Ct. 1916 (2018). This problem of responsiveness has affected voters affiliated with both parties over the course of the decade.

In the 2018 midterm election, the surge in voter enthusiasm and turnout for Democratic candidates did not translate into Democratic electoral gains in States with extreme partisan gerrymanders.⁴ In many States across the country, voter preferences for Democrats resulted in Democratic electoral gains in statewide elections but few gains in district-level elections under

³ 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 will win 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.

⁴ More than 49.3% of the voting-eligible population cast ballots in the 2018 midterm elections. *November General Election Turnout Rates*, United States Election Project, <http://bit.ly/2tNijOt> (last updated Dec. 14, 2018). An estimated 116 million Americans turned out to vote, marking the first time ever that midterm election turnout exceeded 100 million voters. Camila Domonoske, *A Boatload of Ballots: Midterm Voter Turnout Hit 50-Year High*, NPR, Nov. 8, 2018, <https://n.pr/2GZB9JI>.

gerrymandered congressional or state legislative maps.

A. Gerrymandered Districts Diluted Votes in the 2018 “Wave” Elections

In 2018, congressional Democrats won the national popular vote margin 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>. Notwithstanding the 2018 Democratic wave, the election results in many districts were unresponsive to voter preferences. Under responsive maps, higher vote shares in favor of candidates of one party translate into gains in seat shares for that party.⁵ But in 2018, as the percentage of the vote for Democratic candidates rose, the seat distribution under gerrymandered maps largely remained static. In fact, under many of these gerrymandered maps, despite significant fluctuations in party vote share since 2010, seat shares have not changed. The election results in Wisconsin, Ohio, Michigan, and North Carolina provide evidence of this phenomenon, while the results in Pennsylvania, in which

⁵ Estimates indicate that a national 1-point change in the vote for a party should result in about a 2-point change in the percentage of seats for that party. Michael P. McDonald, *Seats to Votes Ratios in the United States* (2009) (unpublished paper) (on file with the Jack W. Peltason Center for the Study of Democracy at the University of California, Irvine), <http://bit.ly/2EhMB0B>; *see also* Laura Royden, Michael Li & Yuriy Rudensky, Brennan Ctr. for Justice, *Extreme Gerrymandering & the 2018 Midterm 6* (2018), <http://bit.ly/2Su4NJq>.

non-politicians redrew gerrymandered lines, provide a counter-example.

Wisconsin. In Wisconsin, Democrats received 205,000 more votes than Republican candidates, but won only 36 of the 99 available seats in the State Assembly. See *2018 Fall Election Results*, Wis. Elections Comm'n, Nov. 6, 2018, <http://bit.ly/2St3hXI>. Republicans have held nearly two-thirds of state legislative seats in Wisconsin since the 2011 passage of Act 43, Wisconsin's redistricting plan. Democrats have held only about one third of assembly seats since 2011—between 35 and 39 seats out of 99—despite receiving statewide vote shares between 48% and 53%. See *Gill v. Whitford*, 138 S. Ct. 1916, 1923 (2018); *2016 Fall Election Results*, Wis. Elections Comm'n, Nov. 8, 2016, <http://bit.ly/2Eprcmf>; Phillip Bump, *The Several Layers of Republican Power-Grabbing in Wisconsin*, Wash. Post, Dec. 4, 2018, <https://wapo.st/2Sq5Ppz>.

While Democrats were unable to make material gains in the gerrymandered State Assembly in 2018, Democratic candidates in statewide elections for Governor and Attorney General defeated Republican incumbents, and a Democratic Senator and Secretary of State were reelected. Bump, *supra*. For the first time since 1982, Democrats in Wisconsin swept all five statewide contests for executive offices. John Nichols, *The States That Elected Trump Have Turned Against Him*, *The Nation*, Nov. 8, 2018, <http://bit.ly/2Xquf6j>. Yet

at the same time Democrats gained only one seat in the gerrymandered State Assembly. Bump, *supra*.⁶

Ohio. In Ohio, Democrats won only four of 16 congressional seats despite receiving nearly 50% of the vote. Rich Exner, *A record turnout, big night for the GOP and gerrymandering's impact: Numbers takeaways from Ohio election 2018*, Cleveland.com, Nov. 7, 2018, <http://bit.ly/2Srcmk4>.

This result is all the more striking given that in 2018, Democrats had improved their performance over the 2016 election cycle by approximately five percentage points, but won only the same four seats that they won in 2016. In fact, notwithstanding the Democratic wave in 2018, the results under the Ohio congressional districts has remained unchanged in every election this decade—the State’s congressional gerrymander has proved to be durable enough to absorb the electoral shifts and preserve the seat share of the mapmakers’ preferred party.⁷ In 2018, the four Ohio districts packed with Democratic voters voted for Democrats by a combined 71% to 29%, while Republicans cracked the

⁶ In Wisconsin’s neighboring State of Minnesota, by contrast, where Democrats won statewide races and the popular vote statewide, the Democratic Party won 77 seats in the Minnesota House to the Republicans’ 57 seats. See Briana Biersbach, *DFL Retakes Minnesota House; MN Senate Stays with GOP*, MPR News, Nov. 6, 2018, <http://bit.ly/2XpFImr>.

⁷ Indeed, Democrats are not even expected to compete for a fifth congressional seat unless their statewide vote share reaches 52.78%, representing a 28.64% jump from the minimum of 26.07% required to gain four seats. Royden, Li & Rudensky, *supra*.

remaining Democratic voters and won their 12 seats by a combined 59% to 40%. Exner, *supra*.

Michigan. In Michigan, Democrats won a majority in vote share in the State Senate, but won 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—thereby 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>.

Biased Michigan results have remained durable throughout the decade. The 2018 midterm election marked the third straight election in which the two parties had near-equal splits of vote share, but the party responsible for the gerrymander retained control of both chambers of the Michigan Legislature. Tom Perkins, *Once again, Michigan Dems get more state Senate and House votes, but GOP keeps power*, Detroit MetroTimes, Nov. 7, 2018, <http://bit.ly/2H8MqHE>; *Quantifying the Level of Gerrymandering in Michigan*, Citizens Research Council of Mich. (June 2018), <http://bit.ly/2Nyzn3O>.

Pennsylvania and North Carolina. The effect of partisan gerrymandering in 2018 is especially apparent when comparing the results in Pennsylvania and North Carolina. At the beginning of the decade, Republicans drew congressional maps in both States to benefit Republican candidates, and the results under both maps exhibited similar partisan bias: In Pennsylvania, Democrats won only the same five seats (out of 18), or 27.7% of the seats, in 2012, 2014, and 2016—despite receiving between 44.46% and 50.28% of the popular vote in each of those years. *See* Karen L. Haas, Clerk of the United States House of Representatives, *Election Statistics, 1920 to Present*, <http://bit.ly/ElectionStats1920-Present> (follow links to years 2012, 2014, and 2016). Similarly, in North Carolina, Democrats won only the same three seats (out of 13), or about 23% of the seats, in 2014 and 2016, despite receiving between 43.95% and 46.6% of the votes in those years.⁸ *Id.*

In the 2018 election, however, the Pennsylvania congressional map was replaced with a new court-drawn map. Democrats in Pennsylvania received 55.5% of the two-party vote, and now hold seats in 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); Lieb, *supra*. As in Pennsylvania, Democratic

⁸ In 2012, Democrats in North Carolina won a fourth seat 50.1% to 49.9%. *See* Haas, *supra*.

candidates in North Carolina performed well statewide⁹—Democratic candidates won every statewide election on the ballot. But Democratic congressional candidates have won only three seats (out of 13)—the same three seats they won in previous years. Lieb, *supra*.¹⁰

B. Both Parties Relied on Modern Gerrymanders to Dilute the Votes of Opposing Party Voters

Republicans and Democrats alike deploy modern gerrymanders to dilute the votes of individual voters in gerrymandered districts. In States in which Democrats created gerrymanders, they were able to hold and even gain seats during the 2014 and 2016 election cycles, notwithstanding Republican gains in the popular vote in those years.

For example, in Maryland, Republicans have controlled only one of Maryland's eight congressional seats (or 12.5% of the seats) since 2011. Republicans

⁹ Democrats in North Carolina earned 48.3% of the total vote in 2018, which represented an increase over their vote share in the 2014 and 2016 elections. Maggie Astor & K.K. Rebecca Lai, *What's Stronger Than a Blue Wave? Gerrymandered Districts*, N.Y. Times, Nov. 29, 2018, <https://nyti.ms/2Stpx3T>; Haas, *supra*.

¹⁰ Based on allegations and evidence of absentee-ballot fraud, North Carolina's Board of Elections did not certify the 2018 results of the McCready/Harris congressional race in North Carolina's Ninth District and has ordered a new election for that District. Amy Gardner, *N.C. board declares a new election in contested House race after the GOP candidate admitted he was mistaken in his testimony*, Feb. 21, 2019, <https://wapo.st/2Tt0aUi>.

have not won more than one congressional seat since 2011 despite wide swings in the congressional statewide Republican vote share in that time period ranging from 32.27% in the 2018 Democratic wave election to 41.36% in the 2014 Republican wave election. *2018 Maryland Election Results*, N.Y. Times, Jan. 28, 2019, <https://nyti.ms/2EyvVmD>.

The voters in Maryland's Sixth Congressional District had elected a Republican for the previous two decades before the enactment of the current maps. Under the new maps, Democrats were able to defeat the Republican incumbent, Roscoe Bartlett, who had held the seat since 1992. While Bartlett won the Sixth District with a 22.28% margin in 2010 (the year before the gerrymander), he lost by a 20.9% margin in 2012, the first election under the current maps. See Maryland State Board of Elections, <https://bit.ly/2Tmfbar> (2010 results), <https://bit.ly/2T5ytlc> (2012 results). Since then, Democrats consistently have won in the Sixth District despite two Republican wave elections in 2014 and 2016. *2016 Maryland House Election Results*, N.Y. Times, Aug. 1, 2017, <https://nyti.ms/2GKPtGH>.

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

Modern partisan gerrymanders resist wave elections because of three phenomena, not all present in

prior redistricting cycles. *First*, partisan affiliation (self-identification with a party) and voter behavior are highly stable and predictable, making the partisan affiliation of voters a dependable trait on which mapmakers can rely. *Second*, a wealth of granular voter data now available to mapmakers enables them to predict voter behavior with an unprecedented degree of accuracy. *Third*, new and advanced statistical and map drawing applications enable partisans to translate voting data and analysis into districts that maximize partisan advantage.

A. Partisan Identity Is Highly Stable and Predictable

As a general matter—and despite suggestions to the contrary¹¹—the partisan identity of voters is highly stable and mapmakers can use data about partisan identity to predict voter behavior with a very high degree of confidence from election to election.¹²

¹¹ See Br. of Amicus Curiae Nat'l Republican Redistricting Trust in Supp. of Appellants 28-29 (“[V]oter choices fluctuate, and party affiliation is not enough to tie the interests of a group to the personal interests of voters for preferred candidates.”); Br. of Amicus Curiae Nat'l Republican Cong. Comm. (“NRCC”) in Supp. of Appellants 21 (“[V]oters’ partisanship, partisan affiliation, political positions, and electoral choices are not immutable.”).

¹² The National Science Foundation funded a panel survey that re-interviewed 9,500 voters in 2010 and 2014. See Brian Schaffner & Stephen Ansolabehere, *2010-2014 Cooperative Congressional Election Study Panel Survey (Version 10)*, Harvard Dataverse (June 10, 2015), <http://bit.ly/2BUbeA5>. The results provide an example of the high stability of partisan identity among voters: only 1% of respondents who identified as Democrats in

Voter predictability enables mapmakers to design maps that survive wave elections, which are largely driven by differential turnout between voters who identify with each party. Daron Shaw, *If Everyone Votes Their Party, Why Do Presidential Election Outcomes Vary So Much?*, 10 *The Forum* 3 (2012).¹³

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. And an individual’s partisan identification is, on average, more enduring and stable than his or her core values or positions on political issues. Paul Goren, *Party Identification and Core Political Values*, 49 *Am. J. Pol. Sci.*

2010 identified as Republicans in 2014 and only 1% of respondents who identified as Republicans in 2010 shifted to Democrats in 2014. *Id.*

¹³ In 2018, for example, 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. Approximately 51.7 million Democrats voted in midterm House races in 2018, compared to 47.4 million Republicans. In 13 States, Democratic vote counts surpassed those of the 2016 presidential election. Dan Keating & Kate Rabinowitz, *Turnout was high for a midterm and even rivaled a presidential election*, *Wash. Post*, Nov. 8, 2018, <https://wapo.st/2U6Gzq4>; Abby Vesoulis, *The 2018 Elections Saw Record Midterm Turnout*, *Time Magazine*, Nov. 13, 2018, <https://bit.ly/2sqvbJq>.

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.* 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. of Pol.* 1253 (Oct. 2017).

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 (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 (2014), <https://pewrsr.ch/2Exx0v4>.

Political scientists also have detected an increase in the *intensity* of party preferences within the electorate. Although enthusiasm for partisans’ own parties has remained relatively stable over time, empirical evidence shows that “partisans like their opponents less and less.” Shanto Iyengar, Gaurav Sood & Yphtach Lelkes, *Affect, Not Ideology: A Social Identity Perspective on Polarization*, 76 *Pub. Opinion Q.* 405, 412-15 (2012); *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).

Increases in intensity across parties since the 1980s have two important implications: 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, 691, 705 (2015). Independent voters are not immune from 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 who 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). Furthermore, 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, independent voters 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>.

One metric that coincides with this shift towards increased and stable partisanship is the decline in split-ticket voting.¹⁴ While split-ticket voting was commonly observed in the 1970s and 1980s, the 2012 election featured record high numbers of voters engaged in straight-ticket voting—that is, voting for the candidate for President from one party and voting for House or Senate members from the same party. See Abramowitz & Webster, *supra*, at 12, 13. The rate of straight-ticket voting in the presidential and House

¹⁴ 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.

elections in 2012 was approximately 89%, up from 70% in 1972, resulting in a relationship between presidential and House election outcomes that was three times stronger than it was in the 1970s. *Id.* at 13, 18. The rate of straight-ticket voting in the presidential and Senate elections in 2012 was approximately 90%, resulting in a relationship between presidential and Senate election outcomes that was similarly much stronger than it was in the 1970s. *Id.* at 13, 19. Nationalized, party-line voting behavior also influences elections for state and local office. Daniel J. Hopkins, *The Increasingly United States: How and Why American Political Behavior Nationalized* (University of Chicago Press 2018).

The decline in split-ticket voting also coincides with a decline 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), culminating in 2016 with only 8% of districts electing a House member from a different party than their preferred presidential candidate, and zero splits in outcome between the Senate and presidential races. See David Hawkings, *The Incredible Shrinking Split Tickets*, Roll Call, Feb. 1, 2017, <http://bit.ly/2IBrtHS>.¹⁵ In fact, 2016 marked the first election since 1914—when the country began electing Senators by popular

¹⁵ 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.

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>.

The concurrent phenomena of stable partisan identity as an indicator of voting preferences, intensifying partisanship, and the decline of ticket-splitting allow mapmakers to rely on the predictability of voter behavior as never before when working to maximize the partisan bias and durability of gerrymanders.

B. Publicly-Available 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 like Civis Analytics 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* 14 (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 additional 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, 883-84 (2012).

The 2018 elections demonstrate the power of using voter records, data, social media and even credit reports to micro-target and track voters. Patterson, *supra*. The 2018 election was marked by 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/2SsqlpR>. During the 2018 Georgia governor’s race, for example, candidate Stacey Abrams eschewed traditional, broad targeting tactics, choosing instead to target an “untapped market” of 90,000 voters that her campaign identified as “persuadable” based on collected data. From the outset, she “targeted her message, the mechanics of her campaign and much of her nearly \$17 million fundraising haul” on these “irregular voters.” Bill Barrow, *Inside Stacey Abrams’ strategy to mobilize Georgia voters*, AP News, Oct. 12, 2018, <http://bit.ly/2NqsIbN>.

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. Civis Analytics, *Data science and the midterm elections: breaking down the results*, Nov. 28, 2018, <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 did not exist in even the recent past.

C. Advanced Analytics and New Statistical Techniques Enable Partisans to Draw Districts for Maximum Partisan Advantage

Advanced analytics and new statistical techniques have allowed mapmakers to optimize voter data to create durable gerrymanders capable of stopping and even reversing the effects of “wave” election years. James Manyika et al., *Big Data: The Next Frontier for Innovation, Competition, and Productivity*, McKinsey Global Institute (May 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. 278 (2018), <http://bit.ly/2BTrnpj>; cf. Editorial, *Gerrymandering failed for GOP in state Senate loss*, Buff. News, Nov. 12, 2018, <http://bit.ly/2U97NfZ>.

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 Citigate 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, <http://bit.ly/2TnXxU0>.

Mapmakers aligned with both Republicans and Democrats used these techniques and technologies to design maps in the most recent redistricting cycle. For example, in North Carolina’s 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)). The maps that emerged from North Carolina's multiple rounds of redistricting this cycle, including court-ordered redistricting, have substantial and durable partisan bias and preserved the Republican Party's 10-3 partisan advantage in North Carolina's congressional delegation, despite a ratio of registered Republicans to Democrats of 0.7 to 1 in 2012 in the electorate. *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>.

Similarly, in Maryland, the Democratic Party leadership retained a consultant who used Maptitude to create different hypothetical districts and gauge potential election results for each configuration based on precinct-level voter registration, voter turnout, and election results. *Benisek v. Lamone*, 348 F. Supp. 3d 493, 517-18 (D. Md. 2018). Under the maps that emerged from this process, Democrats won seven out of eight of Maryland's congressional districts, capturing a historically safe Republican seat in the Sixth Congressional District 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. IN THE ABSENCE OF JUDICIAL INTERVENTION, PARTISAN GERRYMANDERS WILL ONLY BECOME MORE DURABLE AND MORE 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 the decision-making habits of Americans in a more nuanced and accurate way than ever before. When applied to the process of redistricting, 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. Partisans Will Deploy Even More Advanced Data Analytics to Dilute the Votes of Opposition Party Voters

Data analytics have grown more potent in recent times 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 and vendors 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 2022 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 become powerful mapmaking tools because they will allow 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 his or her neighborhood. *Id.* at 127. Such accurate, individualized data at the fingertips of mapmakers will only serve to enhance mapmakers' current abilities to create district maps with extreme partisan bias.

Second, in addition to having access to a greater breadth of information, political vendors are able to

deploy data analysis techniques involving machine-learning, which will allow 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 in order to make inferences about the behavior of individuals. *See id.* at 1157. 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, basic regression 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 between them

and 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 will be better able to process nonlinear nuances within a voting model, such as the above-mentioned relationship between voting and age, and are able to do so with less reliance on the skill of any particular analyst. *See id.*; Olivia Guest, Frank J. Kanayet, and Bradley C. Love, *Cognitive Capacity Limits and Electoral Districting* (Dec. 12, 2018), <http://bit.ly/2TlmXBm>.

B. “Matched-Slice” Gerrymandering Schemes Designed to Maximize Partisan Bias Will Become Possible in the Next Round of Redistricting

The availability of augmented voter files and analytical tools will soon enable mapmakers to prepare maps that are far more biased and durable than historical gerrymanders—including even those drawn during the 2010 redistricting cycle.

A theoretical technique called “matched-slice” gerrymandering can draw election maps in order to 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 mapmakers' perspective if each geographic subdivision within the district contains matched-slice representations—*i.e.*, highly partisan Republican voters are paired with highly partisan Democrat 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 particular 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.*¹⁶ 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 a degree sufficient to withstand “wave” election years with even higher vote differentials than 2018.

IV. SOCIAL SCIENCE PROVIDES OBJECTIVE MEASURES 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

¹⁶ 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 data on individual voters. *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.

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, lower courts can conclude that the 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 (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 (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); *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).

A variant of these modeling techniques is the Markov Chain technique, which involves making billions of small and randomized adjustments to an existing map.

Maria Chikina, Alan Frieze & Wesley Pegden, *Assessing significance in a Markov chain without mixing*, 114 Proc. Nat'l Acad. Sci. 2860 (2017); Benjamin Fifield, Michael Higgins, Kosuke Imai & Alexander Tarr, *A New Automated Redistricting Simulator Using Markov Chain Monte Carlo* (May 24, 2018) (unpublished manuscript), <http://bit.ly/2VqCDRx>. If the vast majority of those random adjustments result in maps that exhibit a reduction in partisan bias when compared to the existing map, they can support a conclusion that the original map is a partisan gerrymander.

Courts and litigants can use computer modeling techniques and social science tools to identify gerrymanders and to 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 many tools now available to identify constitutional violations.



CONCLUSION

For the foregoing reasons, *Amici* respectfully request that the Court rule in favor of Appellees and affirm the judgment in Case Nos. 18-422 and 18-726.

Respectfully submitted,

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