No. 16-1161

IN THE

Supreme Court of the United States

BEVERLY R. GILL, *et al.*,

Appellants,

v.

WILLIAM WHITFORD, *et al.*,

Appellees.

On Appeal from the United States District Court for the Western District of Wisconsin

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

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September 5, 2017

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INTEREST OF *AMICI*[1]

Amici Curiae are all nationally recognized university research scholars and political scientists whose collective 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. *Amici* are among the leading scholars to study the predictability of voter behavior and the mechanisms redistricting mapmakers use to harness data relating to voter behavior and characteristics when preparing redistricting plans. *Amici* are well positioned to predict how recent developments in the availability of data on voters, the capabilities of mapmaking software, and the capacities of data analysis tools are likely to influence the 2020 redistricting cycle and beyond.

INTRODUCTION AND SUMMARY OF ARGUMENT

The past decade has seen an explosion in data gathering and data analytics. This explosion is poised to have a significant impact on mapmaking and plan analysis in the redistricting context.

Mapmakers have at their disposal more data—and more accurate data—about individual voters than ever before. Mapmakers have access to sophisticated

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1 This brief *amici curiae* is filed with the consent of all parties. 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.

analytical software and technology allowing them to leverage this data to predict and exploit voter behavior with a high degree of accuracy. These new and enhanced data and tools—coupled with the demonstrated stability of partisan identity and increasing stability of partisan behavior—allow mapmakers seeking to engineer a gerrymander to sort through a vast array of maps and select those that would entrench the most extreme partisan bias, all without violating historical redistricting principles.[2] As a result, gerrymandering techniques that were only theoretical in the 2010 redistricting cycle could become commonplace in the 2020 redistricting cycle and beyond.

The most recent redistricting cycle already saw less complex versions of these techniques deployed at the national and local level. The use of these techniques corresponded with the emergence of maps that are durably biased, predictably and consistently favoring the party that controlled the redistricting process. In light of intervening developments, however, voters face a future of gerrymanders that are even more biased and more durable, and yet less irregular-looking than ever before. As a result, district shape will be a less reliable guide for identifying an unconstitutional partisan gerrymander.

Crucially for the courts, the tools that enable mapmakers to draw such precise and durable maps also enable factfinders to diagnose the most extreme examples of bias in redistricting. Just as social science and technology have facilitated and will facilitate

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[2] A "durable" gerrymander is one in which the gerrymandering party retains control of the legislature for multiple election cycles spanning the entire decennial period following its implementation of the gerrymander.

partisan gerrymandering, they can be used to identify such gerrymandering when it does occur.

ARGUMENT

I. THIS REDISTRICTING CYCLE HAS FEATURED HIGHLY DURABLE PARTISAN BIAS

After the 2010 Census, congressional and state legislative maps were redrawn en masse. As a whole, the new maps displayed "a sharp increase in partisan bias" as compared to the prior cycle's maps. Anthony J. McGann et al., *Gerrymandering in America* 56, 87, 97 (2016). A subset of the resulting maps have demonstrated extreme and durable partisan bias in favor of one party. *See id.*; Laura Royden & Michael Li, Brennan Ctr. for Justice, *Extreme Maps* 1 (2017) (measuring the performance of Congressional maps over the 2012, 2014, and 2016 elections under three measures of partisan asymmetry); J.A. App. SA224 (Expert Report of Simon Jackman). Mapmakers can intentionally engineer this kind of bias through the redistricting process. They have this ability because voter behavior is both predictable and exploitable through a combination of data gathering, data analysis, and map-drawing techniques and technology. Versions of these data, techniques, and technologies were deployed throughout the 2011 cycle in redistricting processes that generated maps with high bias, including Wisconsin's redistricting process.

A. Voter Behavior Is Predictable and Exploitable, Permitting Mapmakers to Create Intentionally Discriminatory Maps with Durable Bias

Extreme gerrymanders are made possible by three basic facts, which were never found together in prior redistricting cycles. *First*, partisan affiliation and voter behavior are highly stable and predictable, making the partisan affiliation of voters a fact that mapmakers can rely on. *Second*, there is now a wealth of data available to mapmakers about voters that allow them to predict voter behavior with a high degree of accuracy. *Third*, there are new and advanced statistical and map drawing applications that mapmakers can use to prepare maps.

1. Partisan Identity Is Highly Stable and Predictable

As a general matter—and despite suggestions to the contrary[3]—the partisan identity of voters is highly stable and does not change from election to election. This allows mapmakers to rely on partisan identity when preparing gerrymandered maps.[4]

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[3] *See* Br. of Amicus Curiae Nat'l Republican Cong. Comm. ("NRCC") in Supp. of Appellants 42 ("Party affiliation is not set in stone or in a voter's genes . . . ." (quoting J.S. App. 242a (Griesbach, J., dissenting))); Br. of Amicus Curiae Wis. Mfrs. & Commerce ("WMC") in Supp. of Appellants 5 ("[P]arty affiliation may be decisive or it may matter very little."); Br. of Wis. State Senate in Supp. of Appellants 19 ("[E]quating a vote for an individual candidate to a vote for a statewide political party misguidedly assumes that the only factor determining voting behavior is political affiliation.").

[4] To be clear, the literature assessing partisan identity *does not* suggest that individual voters cannot think for themselves, nor does it suggest that partisan identity is the only factor that

Voters are "socialized" into a particular party at an early age, and partisan affiliation tends to harden in early adulthood. *See* Donald Green, Bradley Palmquist & Eric Schickler, *Partisan Hearts and Minds* 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. Indeed, partisan attachment remains among the strongest predictors of voter preferences, trumping sex, class, religion, and often race. *Id.* 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 (2016). In addition, the distribution of partisan identities among the electorate "provides powerful clues as to how elections will be decided." *See* 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 as partisan behavior has become more stable. Based on an analysis of American National Election Studies time-series data, the "observed rate of Americans voting for a different party across successive presidential elections has never been lower." *See* Corwin D. Smidt, *Polarization and the Decline of the American Floating Voter*, 61 Am. J. Pol. Sci. 365, 365-81 (2017). As a result, each party has a

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influences votes or that individual voting behavior can be predicted with absolute certainty. The social science *does* establish that data about partisan identity can be used to predict voter behavior with a very high degree of confidence and that partisan identity is stable over time.

reliable and predictable "base of party support that is less responsive to short-term forces." *Id*.

There also has been a measurable increase in the *intensity* of party preferences within the electorate, what is popularly referred to as "polarization"; 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). 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), http://www.people-press.org/files/2014/06/6-12-2014-Political-Polarization-Release.pdf. Uniform increases in affective polarization 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." *See* Shanto Iyengar & Sean J. Westwood, *Fear and Loathing Across Party Lines: New Evidence on Group Polarization*, 59 Am. J. Pol. Sci. 690, 691, 705 (2014).

Independent voters are not immune from the effects of partisan intensity, since "[m]ost of those who identify as independents lean toward a party." Pew Research Ctr., *A Deep Dive into Party Affiliation* 4 (2015), http://www.people-press.org/files/2015/04/4-7-

2015-Party-ID-release.pdf. 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*, The Forum, Oct. 2012, Article 6, at 1, 17. 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), http://assets.pewresearch.org/wp-content/uploads/sites/5/2016/06/06-22-16-Partisanship-and-animosity-release.pdf.

One metric that coincides with this shift towards increased partisanship is the well-documented decline of split-ticket voting.[5] 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 elections in 2012 was approximately 89%, 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

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[5] 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.

in 2012 was approximately 90%, resulting in a relationship between presidential and Senate election outcomes that was more than twenty-five times stronger than it was in the 1970s. *Id.* at 13, 19. This sort of party line voting also applies to statehouses. *See, e.g.*, Steven Rogers, *National Forces in State Legislative Elections*, 667 Annals Am. Acad. Pol. & Soc. Sci. 207, 207-09, 220-22 (2016).

The decline in split-ticket voting 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). *See* David Hawkings, *The Incredible Shrinking Split Tickets*, Roll Call (Feb. 1, 2017, 7:04 AM), http://www.rollcall.com/news/hawkings/polarized-politics-split-tickets-midterms.[6]

Occasional or isolated instances of districts changing party over two election cycles—or split outcomes in a single election cycle—are ultimately immaterial. Regardless of any individual examples of these phenomena,[7] the consistency in partisan behavior from election to election, and the decline in split-ticket voting, are both well documented in the social science literature, as discussed above.

The concurrent phenomena of stable partisan identity as an indicator of voting preferences, intensifying partisanship, and the decline of ticket-splitting means that mapmakers are able to rely on

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[6] 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* Section I.A.2.

[7] *See* Br. of NRCC 42-44; Br. of WMC 6.

the predictability of voter behavior when working to maximize the bias and durability of gerrymanders.

2. Mapmakers Have Been Able to Assess Partisan Affiliation Through Publicly Available Records That Provide Granular Indicia of How Particular Voters Will Behave

During the 2010 redistricting cycle, mapmakers had access to a wealth of publicly available information about individual voters.[8] The quantity and granularity of voter data that has become available in recent years is unprecedented, and allows mapmakers to assess and predict partisan affiliation more accurately than ever.[9] Political campaigns have always tried to predict the partisan affiliation of potential voters, but in recent years, political actors have increasingly relied on statistics and predictive analytics for use in campaigns. *See* David W. Nickerson & Todd Rogers, *Political Campaigns and Big Data*, 28 J. Econ. Persp. 51, 59 (2014) (observing that, as recently as a decade or two ago, political campaigns used techniques "to predict the tendencies of citizens [that] appear extremely rudimentary by current standards"). Although campaigns historically possessed considerable information drawn from census information and their

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[8] There are some variations in the quantity and quality of individual voter data from state to state.

[9] Of course, mapmakers in many jurisdictions work with units larger than an individual, and much of redistricting is based on predictions about how *groups* of voters in small areas will behave. Those predictions, in turn, are based on aggregate data regarding individual voter affiliation and voter behavior in those small areas.

own volunteers, they lacked the reams of data and computing power made available by modern technology. *Id.* at 52.

The increase in available public data has coincided with the rise of detailed voter databases, referred to as "augmented voter files," which compile and curate this data for use by political campaigns. *See* Eitan D. Hersh, *Hacking the Electorate: How Campaigns Perceive Voters* 67 (2015). Augmented voter files contain traditional voter registration records that have been processed through data cleaning services and matched with substantial additional information, including but not limited to census data, consumer data compiled and sold by businesses, voter information collected by political campaigns, political contribution history, and even analytic scores designed to predict voters' particular political characteristics. *See id.* at 66-69; 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); Ira S. Rubinstein, *Voter Privacy in the Age of Big Data*, 2014 Wis. L. Rev. 861, 875-78. These types of augmented voter files—which are compiled by companies such as Catalist, Aristotle, and Voter Vault—are increasingly common resources available to political campaigns and mapmakers.[10]

[10] There is anecdotal evidence that individualized voter data contained in augmented voter files may have been used by mapmakers in the 2010 cycle for the purpose of crafting gerrymanders. *See* Christopher S. Elmendorf, *From Educational Adequacy to Representational Adequacy: A New Template for Legal Attacks on Partisan Gerrymanders* 44 n.222 (Feb. 22, 2017), http://www.ssrn.com/abstract=2916294.

For example, Catalist—which provides augmented voter files predominantly for Democrats and progressive organizations—incorporates 700 different variables in its database, including "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." Evans, *supra*, at 883. This information, of course, has uses beyond predicting voter behavior. Campaign clients can input any number of desired variables to make custom lists of voters they can then microtarget through emails, calls, and online political advertising. *See* Hersh, *supra*, at 71.

Catalist and other vendors use analytical models to assign a "continuous predictive score" to each citizen, giving clients "a prediction of partisanship and a prediction of turnout likelihood." *Id.* at 72. This can be especially useful in determining the potential turnout of independent voters. As Professor Hersh notes:

> Suppose a voter is registered independent, but in the analytics sample this voter is listed as likely married to someone else who is a registered Democrat. Catalist might predict that this type of independent voter leans Democratic.

Id. at 71. Catalist and other organizations further improve their predictive accuracy through the proprietary data given to them by clients, such as membership lists:

> [I]f someone is registered independent but is a member of a pro-choice group and has told an Obama volunteer that he or she is

> supporting Obama, then Catalist might use these data points to predict that this person, despite being a registered independent, is likely to be a Democratic supporter.

Id. at 72. This combination of volunteered proprietary data and existing census and consumer data as inputs into potent prediction models allows campaigns to determine partisan affiliation and voter preferences at a level of precision that did not exist even in the recent past.

3. Statistical Techniques and Map-Building Technologies Have Provided Mapmakers with the Means to Operationalize Their Knowledge of Voter Behavior and Create Durably Biased Maps

During the 2010 redistricting cycle, mapmakers not only had access to expansive data sets that allowed them to accurately predict voter behavior, but they also had access to new and/or improved redistricting software. This software, combined with modern statistical techniques, allowed mapmakers to tailor durably biased maps.

One of the most popular of these tools is "Maptitude for Redistricting," a program offered by Caliper Corporation, which advertises that "[i]t is used by a super-majority of the state legislatures, political parties, and public interest groups." Caliper, *Maptitude Software, Data, and Services for Redistricting* 1 (2016), http://www.caliper.com/PDFs/Maptitude%20for%20Redistricting%20Brochure.pdf.[11] Similar to the data

[11] Caliper Corporation offers a complete range of Maptitude products to assist those involved at all stages of the redistricting and electoral process. In addition to "Maptitude for Redistricting," Caliper offers Political Maptitude for campaigns,

analytics used by political firms to create voter databases, "*Maptitude* allows a user to control for virtually every possible factor or outcome affecting or resulting from redistricting, including past election results, compactness, population deviation, race, communities of interest, and past legislative apportionment plans." *See* Matthew LaGarde, *In Re 2012 Legislative Redistricting: Maryland High Court Decision Exemplifies Lackluster Federal Guidance on Redistricting*, 74 Md. L. Rev. 653, 674 (2015).

Maptitude is not the only software available to mapmakers. ESRI produces software that allows its users to leverage geographic and demographic data about voters and prepare biased maps with precision. ESRI's products are easy to use, and, like Maptitude, even allow novice software users to quickly and easily develop redistricting plans based on customizable data sets, including data that predicts the projected partisan affiliation of voters. *See Elections*, ArcGIS for Loc. Gov't, http://solutions.arcgis.com/local-government/elections/ (last visited Aug. 30, 2017).

Mapmakers aligned with Republicans and those aligned with Democrats used similar techniques and technologies in crafting maps in the most recent redistricting cycle. Maptitude, for example, was used in North Carolina's redistricting process by a consultant retained by the leadership of the state's

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which is used by political campaigns to fine-tune campaign strategy and deploy resources, as well as Maptitude for Precinct and Election Management, which is used by many local government agencies to draw election districts and manage lists of voters. *See* Caliper, *Political Maptitude* (2002), http://www.caliper.com/pdfs/politicalmaptbrochure.pdf; Caliper, *Maptitude for Precinct and Election Management* (2011), http://www.caliper.com/PDFs/MaptitudePEBrochure.pdf.

Republican Party. *See* Findings of Fact and Conclusions of Law Filed by the *Common Cause* Plaintiffs at 8, 40, *Common Cause* v. *Rucho*, No. 1:16-CV-1026-WO-JEP (M.D.N.C. June 5, 2017). In North Carolina, Maptitude was loaded with past election data, allowing the consultant to view the data, assign to it a color "thematic" that would show "the partisan voting history of a given unit of geographical area, most importantly at the level of a single voter district." *Id.* at 8. After color coding Democratic or Republican voter districts and counties, the consultant "then assigned them to districts that were designed to maintain the Republican Party's 10-3 partisan advantage." *Id.* at 40. The maps that emerged from North Carolina's multiple rounds of redistricting this cycle, including court-ordered redistricting, have displayed substantial and durable bias. *See id*. at 2-4; Royden & Li, *supra*, at 1, 6, 9.

Similarly, in Maryland, Democratic party leadership retained NCEC Services, a D.C.-based analyst group, to create a gerrymandered map in the wake of the 2010 census. Memorandum in Support of Plaintiffs' Rule 65(a) Motion for a Preliminary Injunction and to Advance and Consolidate the Trial on the Merits, or, in the Alternative, for Summary Judgment at 6-7, *Benisek* v. *Lamone*, No. 13-cv-3233 (D. Md. May 31, 2017). Using mapping software, census data, and partisan voting algorithms, NCEC Services designed a map with an eye to guaranteeing that at least seven Democrats would be elected each Congressional term. *See id.* at 12. The team of analysts had access to substantial information when building the map, including precinct-level voter registration, voter turnout, and election results for primary and general elections for each level of government. *Id.* at 4. The analysts were then able to link these extensive data to Maptitude to create different hypothetical districts and gauge potential election results for each configuration. *Id.* at 7. Each map was evaluated according to its predicted Democratic performance, and the NCEC team created a spreadsheet comparing various map results. *Id.* at 8, 10. Moreover, any NCEC consultant could manipulate the map in real time and solicit feedback from party leadership based on how the districts shifted and how the projected results varied. *Id.* at 9-10. Under the maps that emerged from this process, Democrats won seven out of eight of Maryland's congressional districts. In Maryland's Sixth congressional district, which was historically a safe Republican seat, the Democrats won by 21-points—the largest redistricting swing of any congressional district in the country. *Id*. at 27.

B. Wisconsin's 2011 Assembly Map Is a Product of Contemporary Gerrymandering Techniques

Wisconsin's Act 43—the subject of this case—was the product of similar techniques and technologies. After the 2010 election, when the voters of Wisconsin elected a Republican majority, the Republican leadership retained a team of lawyers, consultants, and political scientists to redraw Wisconsin's congressional map. J.S. App. 12a-14a.

Wisconsin's redistricting team—like many redistricting teams in the most recent cycle—prepared maps using modern redistricting software that made use of demographic and political data. Wisconsin's redistricting software, AutoBound, like other redistricting software discussed *supra* Section I.A.3, allows its users to draw different district boundaries with "customized demographic data." J.S. App. 17a (internal quotation marks omitted). That data included a "composite partisan score," a metric the redistricting team developed to "assess the partisan make-up" of election districts. J.S. App. 17a. These scores were based on the analysis of past election results throughout the state and were "tested . . . against . . . [a] regression model" prepared by a social scientist "to assess the partisanship of . . . Assembly maps." J.S. App. 14a-17a. Using their "composite score," the redistricting team was able to "evaluate the statewide maps that they had drawn based on the level of partisan advantage that they provided to Republicans." J.S. App. 19a. They collected the partisan outcomes of each map in a spreadsheet for comparison purposes. J.S. App. 19a-20a.

In addition, for each potential map, the team computed an "S" curve[12] to "show how each map would operate within an array of electoral outcomes." J.S. App. 22a. This technique allowed Wisconsin's redistricting team to test various maps and predict, with a high degree of confidence, whether a map would allow Republicans to retain control of the Assembly even in hypothetical years when Democrats perform well across the state.

The redistricting team presented a series of maps to Republican leadership, who selected what they called the "Team Map"—a map designed to ensure that Republicans would maintain a majority under "any likely voting scenario." J.S. App. 24a-27a. Under the Team Map, the Republicans "would maintain a 54 seat majority while garnering only 48% of the statewide

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[12] The "S" curve technique provided a visual depiction of how each party's vote share in a hypothetical election would translate to the number of Assembly seats that party would secure under the given map scenario. J.S. App. 22a.

vote. The Democrats, by contrast, would need 54% of the statewide vote to capture a majority." J.S. App. 27a. The redistricting team believed that they had engineered a map that would entrench Republican control for the decade. As notes prepared by one of the members of the redistricting team for a presentation to the Republican caucus stated, "[t]he maps [the legislature was set to] pass will determine who's here 10 years from now." J.S. App. 28a.

In 2012, under the maps that emerged from this process, Democrats won 51.4% of the two-party vote, yet won only 39 seats in the 99 seat legislature (39.4%). *See* J.A. App. SA184, SA249 (Expert Report of Simon Jackman); *Canvass Results for 2012 Presidential and General Election*, Wisconsin Elections Commission (Nov. 6, 2012), http://elections.wi.gov/sites/default/files/Amended%20Percentage%20Results-11.6.12%20President.pdf. Republican control has proven to be durable under these maps, as the Republicans have retained and expanded their majority in the subsequent years. *See Canvass Results for 2012 Presidential and General Election*, *supra*.

II. PARTISAN GERRYMANDERS WILL ONLY BECOME MORE EXTREME IN THE ABSENCE OF JUDICIAL INTERVENTION

As powerful as current methods are, predictive modeling and other large-scale analytical tools will become even 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 to a more nuanced and accurate level 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 less irregular-looking.

A. Because of Advances in Data Analytics, Corporations and Scientific Researchers Are Able to Predict Individual Human Behavior with Substantial Accuracy

Businesses and scientific researchers provide a salient indicator of how data analytics will be leveraged for political purposes. Like a political party, these entities are interested in predicting the behavior of a large subset of individuals. *See* Max N. Helveston, *Consumer Protection in the Age of Big Data*, 93 Wash. U. L. Rev. 859, 869-70 (2016). "Nearly every business and governmental entity collects information that is (or could be) used in" large-scale data analysis, and both groups have been able to generate individualized, predictive models of human behavior of the sort political actors will use. *See id.*

In recent years, computer performance has improved exponentially as a result of engineering innovation. *See* M. Mitchell Waldrop, *More than Moore*, 530 Nature 144, 145 (2016).[13] Harnessing this massive

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[13] While most off-the-shelf desktop computers available to consumers in 2001 could perform up to 6 billion operations per second, the average laptop in 2012 was capable of tackling 50 billion operations in the same fraction of time. *Compare* Glenn J. McLoughlin & Ian F. Fergusson, Cong. Research Serv., *RL31175, High Performance Computers and Export Control Policy: Issues for Congress* 3 (2003), *with* Matthew U. Scherer, *Regulating Artificial Intelligence Systems: Risks, Challenges, Competencies, and Strategies*, 29 Harv. J.L. & Tech. 353, 375 n.81 (2016). Computer performance continues to improve as different processor "cores" on each microprocessor chip can be put to work on different parts of a single task at the same time. *See* Brian Hayes, *Built for Speed: Designing Exascale Computers*, Topics

improvement in computing power, as well as advances in data mining and analytics, businesses have been able to predict individual consumer behavior with remarkable confidence. *See* Omer Tene & Jules Polonetsky, *Big Data for All: Privacy and User Control in the Age of Analytics*, 11 Nw. J. Tech. & Intell. Prop. 239, 239, 245-50, 253-54 (2013) [hereinafter Tene & Polonetsky, *Big Data for All*]; *see also* Omer Tene & Jules Polonetsky, *Privacy in the Age of Big Data: A Time for Big Decisions*, 64 Stan. L. Rev. Online 63, 64-65 (2012). For years, corporations have used advanced analytical tools to learn about their customers' general preferences, to aid in their purchasing decisions, and to gather marketing data. *See* Tene & Polonetsky, *Big Data for All*, *supra*, at 243-50, 253-54. However, corporations can now also predict increasingly subtle attributes of their consumers in order to optimize purchasing decisions. For example, traditional brick and mortar retailers can now study customer foot movements and the time spent in various aisles in order to optimize their store layout, their mix of goods, and the shelf position of their products. *Id.* at 249. Corporations are now even able to deduce intimate personal details about their customers by comparing their purchasing decisions with those of thousands of other consumers. *See* Charles Duhigg, *How Companies Learn Your Secrets*, N.Y. Times (Feb. 16, 2012), http://www.nytimes.com/2012/02/19/magazine/shopping-habits.html (featuring a Target employee concluding that a customer who bought "cocoa-butter lotion, a purse large enough to double as a diaper bag,

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(Harvard Sch. of Eng'g & Applied Scis., Cambridge, Mass.), Summer 2014, http://www.seas.harvard.edu/news/2014/07/built-for-speed-designi ng-exascale-computers.

zinc and magnesium supplements and a bright blue rug" has an 87% chance of being pregnant).[14] Similarly, scientific researchers have leveraged advances in data analytics to discover unintuitive and nonlinear relationships between data and human behavior. For example, by analyzing over-the-counter sales of healthcare remedies such as cough medicine, health officials are able to anticipate short-term trends in illness transmission. Tene & Polonetsky, *Big Data for All*, *supra*, at 246.

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 nuanced data analysis techniques.

First, businesses and other entities have access to a greater amount of raw data about consumers. Corporations can either gather their own data, or work with firms who specialize in gathering and analyzing consumer purchasing information. These "data brokers," ranging from startups to established entities such as Acxiom, allow a client to purchase vast amounts of their consumers' personal information. *See* Fed. Trade Comm'n, *Data Brokers: A Call for Transparency and Accountability* 7-9 (2014), https://www.ftc.gov/system/files/documents/reports/data-brok

[14] Some corporations base product offerings on predictive modeling. The popular television show *House of Cards* was created in part because Netflix—its producer—realized that there was a large cross section of viewers who enjoyed works directed by David Fincher, House of Cards' Executive Director, and Kevin Spacey, the show's lead actor. *See* David Carr, *Giving Viewers What They Want*, N.Y. Times (2013), http://www.nytimes.com/ 2013/02/25/business/media/for-house-of-cards-using-big-data-to-gu arantee-its-popularity.html.

ers-call-transparency-accountability-report-federal-trade-commission-may-2014/140527databrokerreport.pdf; Neil M. Richards & Jonathan H. King, *Big Data Ethics*, 49 Wake Forest L. Rev. 393, 404-05 (2014). Data brokers aggregate information about individuals from public sources and then use analytical techniques to discern patterns in consumer behavior. *See* Fed. Trade Comm'n, *supra*, at 3; Richards & King, *supra*, at 404-05. These public sources can include traditional offline records such as criminal records, corporate filings, credit agency reports and the like, but they can also include nontraditional avenues of information. *See* Fed. Trade Comm'n, *supra*, at 11-15; Richards & King, *supra*, at 404 ("To obtain their information, data brokers search through government records, purchase histories, social media posts, and hundreds of other available sources."). For example, firms are now able to gather information from consumers not only from standard online sources such as "email, video, images, clickstream[s], logs, search queries," but also from "electric grids, [GPS], roads and bridges" and even from "homes, clothing, and mobile phones." *See* Tene & Polonetsky, *Big Data for All*, *supra*, at 240.

Second, in addition to having greater access to raw data, new data analysis techniques allow businesses or other research entities to discover new trends and correlations. In particular, a crucial and relatively new analytical method is the use of "machine learning" algorithms. "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). Although machine learning was a term coined in the early 1960s, it has only recently become widely applied to analyze large-scale data sets due to the advances in modern computer power and storage efficiency. *See id.* at 1149-50, 1166. Machine learning algorithms are able to leverage large amounts of data and numerous variables to make inferences about the behavior of individuals. *See id.* at 1156-57. When using traditional statistical techniques, scientific researchers or analysts make predictions by designing models based on a specific and limited set of explanatory (or independent) variables and outcome (or dependent) variables. *See id*. By contrast, machine learning algorithms are able to determine which variables are relevant for predictive purposes, and can make predictions using many more characteristics of individuals than would be possible with traditional statistical methods. *See id.*

In addition to outperforming traditional methods in predictive accuracy and efficiency, modern machine learning algorithms are particularly suited for analyzing complex data sets. Because they are not reliant on having rigid pre-defined assumptions to forecast a model, machine learning algorithms can be applied to complex data sets to draw conclusions where previous techniques (e.g., relying on human intuition and simpler regression techniques) fall short. *See id.* at 1158-59. For this reason, companies have relied on machine learning algorithms for core business functions. Many of the features that online shopping and entertainment companies use to "suggest" new products to consumers are based on predictive models created by machine learning algorithms. *See id.* at 1149, 1160. Machine learning has also been used for other complicated tasks, such as automatically sorting mail by predicting the zip codes written on envelopes or preventing self-driving cars from crashing. *Id.* at 1160, 1162.

B. The Same Tools Employed in Business and Science Will Be Deployed to Enable Optimal Gerrymandering Schemes That Also Comply with Traditional Redistricting Principles

Advances in the data sciences will not be confined to commerce and science. Armed with the newest wave of analytical tools, partisan mapmakers will be able to make maps that are more biased and more durable than historical mapmakers—all while satisfying historical redistricting principles.

1. Political Parties Will Leverage the Same Developments in Data Analytics That Have Benefitted Commercial and Scientific Enterprises

Like their corporate counterparts, political parties are interested in leveraging advancements in data analytics. It is unsurprising, then, that the same trends behind new data analytical techniques found in business and science—(1) new access to voluminous public information and (2) advanced analytical techniques such as machine learning— are also being deployed to analyze voter behavior. This is made possible by massive increases in computing power and data storage capacity, which have expanded by orders of magnitude the scope of information available and the technological capacity to analyze that information. *See* Tene & Polonetsky, *Big Data for All*, *supra*, at 239.

First, political data vendors are growing increasingly sophisticated in their ability to collect public voter information and create augmented voter files. While it is already common practice for a party or a campaign to aggregate large amounts of voter information, augmented voter files differ from older compilations of data because they are supplemented with nuanced predictions about individual voter behavior and political preferences. *See supra* Section I.A.2; *see also* Christopher S. Elmendorf, *From Educational Adequacy to Representational Adequacy: A New Template for Legal Attacks on Partisan Gerrymanders* 43 (Feb. 22, 2017), http://www.ssrn.com/abstract=2916294. These augmented files have only recently emerged in part because large-scale, public voter information was not available until the mid-2000s. Neither major political party had completed its first rudimentary voter databases until 2002, and states had not completed their own voter databases until mid-2008. *See* Hersh, *supra*, at 67 (noting that Republicans completed their first voter database in 2002, and Democrats in 2004). Political parties have thus only recently been able to analyze information from these compilations.

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, as discussed *supra* Section I.A.2, variables from detailed public records and proprietary client data can now be used to determine whether individual independent voters previously classified as neutral should instead be classified as leaning toward one party. *See id.* at 71-72. An augmented voter file may also allow mapmakers to predict information that is not recorded publicly. 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. Vendors are able to draw similar connections across a number of demographic variables. *See id.* at 127, 169-75. 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 like machine learning, which will allow them to recognize previously undiscovered individual voting patterns. *See supra* Section II.A. 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. Basic regression techniques can handle a few variables, but they often struggle when confronted with complicated relationships involving a large number of variables. *See id.* at 59-60. In the context of voter behavior, relationships between variables are often nonlinear and context-dependent. *Id*. at 59-61. Any simple regression analysis must account for demographic nuances that affect when certain metrics are useful and when they are not. *Id.* 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. Accordingly, because of nuances like this, past predictive models of individual voter behavior were less accurate than models that are now available to mapmakers. *See id.* at 59-61; *see also* Coglianese & Lehr, *supra*, at 1158-59 (noting that machine learning algorithms "outperform standard procedures in terms of predictive accuracy and statistical efficiency").

Modern machine learning algorithms, however, do not suffer from these drawbacks. Just as they have altered how businesses can extract the most useful meaning from complicated data sets, machine learning algorithms will be more efficient at modeling political data. *See* Nickerson & Rogers, *supra*, at 60-61; *see also* Coglianese & Lehr, *supra*, at 1158-59. 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* Nickerson & Rogers, *supra*, at 59-61. Moreover, they will be more cost effective to deploy, as they do not need the same intensive customization that traditional regression analysis requires.

2. *"Matched-Slice" Gerrymandering Schemes Designed to Maximize Partisan Bias Will Become Possible in the Near Future*

Due to augmented voter files and analytical techniques now available to mapmakers, it may soon be possible for mapmakers to prepare maps that are far more biased and durable than historical gerrymanders—including those drawn during the 2010 redistricting cycle. There is already a body of scholarly literature explaining "matched-slice" gerrymanders—a new theoretical technique for crafting gerrymanders in order to maximize partisan bias. *See, e.g.*, John N. Friedman & Richard T. Holden, *Optimal Gerrymandering: Sometimes Pack, but Never Crack*, 98 Am. Econ. Rev. 113, 134-35 (2008). Historically, matched slicing was not possible because it relies on accurate, individualized knowledge of voter behavior. Elmendorf, *supra*, at 43-44.

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, etc. *Id*. at 43. Although somewhat counter-intuitive, matched slicing strategies are optimal because they neutralize a party's most reliable voters. For example, if a group of strong Republicans 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 strong Democrats. *See* Friedman & Holden, *supra*, at 113, 135. Over time, this "matched slice" strategy will produce optimal partisan results because it most efficiently distributes a party's base of partisan voters. *See id*.; *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 meaningfully process that data into predictive data in order to use matched-slice strategies. *See* Elmendorf, *supra*, at 43-44. Instead, mapmakers relied on broader, geographic-based proxies, such as looking at ward-level data of voter preferences. *See id.* at 44-45.[15]

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[15] 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 mere 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.

With the proliferation of individualized voter data, future mapmakers using the matched-slice technique will be able to maximize partisan bias and durability.

3. *Future Redistricting Efforts Could Result in Maps That Are Even More Durably Biased While Complying with Traditional Mapmaking Principles*

Future gerrymanders could be designed to maximize partisan bias and durability while comporting with traditional redistricting principles.[16] Consequently, relying on the bizarre shapes of districts to identify partisan gerrymanders would result in a test that is both under- and over-inclusive.[17] With advances such as the augmented voter file and machine learning algorithms, aided by new techniques such as the matched-slice gerrymander, mapmakers can form districts that might *appear* to comport with

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Historically, it was not possible to reliably ensure this distribution due to the difficulty in obtaining sufficiently robust and precise data on individual voters. *See* Elmendorf, *supra*, at 43-44. 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.

[16] Many states have constitutional provisions setting forth redistricting criteria. These criteria may vary widely from state to state and may include, among other things, compactness, contiguity, keeping communities of interest together, and respecting political subdivisions. *See* Brennan Ctr. for Justice, *A 50 State Guide to Redistricting* (2011), http://www.brennancenter.org/publication/50-state-guide-redistricting/.

[17] *Contra* Br. of NRCC 19-28; Br. of Amicus Curiae Republican Nat'l Comm. in Supp. of Appellants 2-4, 13-22; Br. of Wis. Inst. for Law & Liberty in Supp. of Appellants 22-28.

historical districting principles when they are in fact designed to entrench and expand partisan bias.

In future redistricting cycles, mapmakers will be able to leverage recently developed techniques for simulating hypothetical maps in order to achieve particular goals.[18] Future mapmakers, who will have access to unprecedented computing power, will be able to prepare thousands of simulated maps and identify the district configurations that can maximize partisan bias and durability while simultaneously comporting with traditional districting principles.

Furthermore, as a result of these advances, practical constraints on gerrymanders that previously may have limited partisan bias will no longer play a significant role. In redistricting cycles prior to the 2010 cycle, gerrymanders had a self-limiting quality, because the more seats the gerrymandering party stacked in their favor, the more vulnerable that party would become in the event of a tide against that party. In other words, seat maximization had a trade-off with risk. *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, 183-84 (Peter Galderisi ed., 2005); *see also Davis* v. *Bandemer*, 478 U.S. 109, 152 (1986) (O'Connor, J., concurring). Contemporary and future gerrymanders are not likely to be self-limiting in the same way as historical gerrymanders. *See, e.g.*, Br. of Bernard Grofman and Ronald Keith Gaddie as Amici Curiae in

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[18] While most academic literature has focused on such simulations as tools to assess partisan bias, *see infra* Section III.B, these same technological tools could easily be used by mapmakers.

Supp. of Neither Party 17 n.5 (explaining that "dummymanders" have become uncommon in part because "the newest, computer-driven redistricting now allows map drawers to make very precise refinements to district lines down to the census-block level. With this sophisticated new technology, map drawers can fashion maps that eliminate meaningful competition for most districts. . . . [G]errymandered victory margins are no longer so thin that they risk disappearing"). The ability to draw biased and durable gerrymanders with more precision, combined with the decline in the number of swing voters, vitiates the traditional trade-off: No plausible tide will overcome the imbalance in districts.

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

Even as software and social science techniques equip mapmakers to create maps with extreme and durable partisan bias, these same types of techniques could also help provide a workable judicial solution to the problem of partisan gerrymandering. In the intervening years since the Court last visited these issues in *Vieth* v. *Jubelirer*, 541 U.S. 267 (2004) and *LULAC* v. *Perry*, 548 U.S. 399 (2006), political scientists have developed a wealth of modern social science techniques that can serve as objective, verifiable, and reliable tools to discern unconstitutional partisan gerrymanders.

In this case, the Court need not endorse one of the many social science measures that are available. Rather, as the Court has done in other redistricting contexts, the Court may set a doctrinal standard that will permit the lower courts to field the best, most current social science evidence to help identify constitutional violations.

For example, in *Thornburg* v. *Gingles*, the Court granted lower courts the flexibility to develop the doctrine of impermissible race-based redistricting. *See* 478 U.S. 30, 58 (1986). In *Gingles*, the Court determined that an inquiry into racially polarized voting would be an essential component of any vote dilution case in the context of racially motivated redistricting; however, the Court declined to embrace any specific test for the existence of legally significant racially polarized voting, choosing instead to set out "general principles" in order to "provide courts with substantial guidance in determining whether evidence" of racially polarized voting "rises to the level of legal significance under" the Voting Rights Act. *Id*.

Here, too, the Court could easily set out general principles to guide lower courts in assessing constitutional violations in the context of partisan gerrymandering. *See, e.g.*, Br. of Grofman & Gaddie 10-22 ("There is consensus among social scientists that three discrete concepts are critical to detecting and measuring the extent of an unconstitutional partisan gerrymander: (1) partisan asymmetry, (2) lack of responsiveness of electoral outcomes to changes in voter decisions, and (3) causation."). With the assistance of expert opinions, lower courts could consider the many analytical and statistical tools that are at their disposal and that could help identify partisan bias in maps. Using those tools in a manner consistent with any principles laid out by the Court, lower courts could distinguish unconstitutional partisan gerrymanders from constitutional maps.

Some of these tools involve simple math; others leverage statistics, enhanced data analysis techniques, and/or cutting-edge computing power. What they all have in common, however, is that none of these robust social science techniques had been developed when the Court last considered this question in *Vieth* and *LULAC*. In addition, these techniques are far superior to historical approaches that have been relied upon to identify maps that were drawn with unconstitutional intent. For example, the Court has recognized that neither a failure to adhere to traditional districting principles nor the presence of irregular lines is a consistent indicator of plans that were drawn with unconstitutional intent. *See Bethune-Hill* v. *Va. Bd. of Elections*, 137 S. Ct. 788, 799 (2017) ("[A] State could construct a plethora of potential maps that look consistent with traditional, race-neutral principles. But if race for its own sake is the overriding reason for choosing one map over others, race still may predominate."); *see also Cooper* v. *Harris*, 137 S. Ct. 1455, 1473-74 (2017). This makes it all the more important for the Court to create a doctrinal space where lower courts could consider advanced social science to provide objective, verifiable, and reliable measures of partisan bias in maps.

A. Contemporary Social Science Provides a Range of Methods to Detect Partisan Bias

The efficiency gap is one metric that could be utilized by courts to detect partisan bias. *See* Nicholas O. Stephanopoulos & Eric M. McGhee, *Partisan Gerrymandering and the Efficiency Gap*, 82 U. Chi. L. Rev. 831, 899-900 (2015). A number of courts (including the court below) have already utilized the efficiency gap in order to assess partisan gerrymandering claims. *See* J.S. App. 159a-176a; *see also Common Cause* v. *Rucho*, No. 1:16-CV-1026, 2017 WL 876307, at *3, *11 (M.D.N.C. Mar. 3, 2017).

Other social science tests that can be used include, but are not limited to, the excess seats test (which identifies when the outcome after redistricting was disproportionally in favor of the redistricting party when compared to a simulated seats/votes curve), the lopsided outcomes test (which measures the difference between the share of Democratic votes in the districts that Democrats win and the share of Republican votes in the districts that Republicans win), and the mean-median difference (which identifies when a party's median vote share is substantially below its average vote share across districts in a state). *See, e.g.*, Samuel S.-H. Wang, *Three Tests for Practical Evaluation of Partisan Gerrymandering*, 68 Stan. L. Rev. 1263, 1306-07 (2016); Michael D. McDonald & Robin E. Best, *Unfair Partisan Gerrymanders in Politics and Law: A Diagnostic Applied to Six Cases*, 14 Election L.J. 312, 328-29 (2015).

B. Computer Simulations Provide Additional Tools to Assess Partisan Bias

Computer simulations can also be used to help identify highly biased maps. Computer simulations can randomly generate a large number of alternative redistricting plans that adhere to traditional redistricting criteria; if the actual plan is more extreme than all or almost all of the plans the computer has drawn, based on one or more social science methods discussed *supra* Section III.A, lower courts can conclude that the traditional criteria do not explain the plan. *See* 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); Yan Y. Liu, Wendy K. Tam Cho & Shaowen Wang, *PEAR: A Massively Parallel Evolutionary Computation Approach for Political Redistricting Optimization and Analysis*, 30 Swarm & Evolutionary Computation 78 (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); Jowei Chen & Jonathan Rodden, *Cutting Through the Thicket: Redistricting Simulations and the Detection of Partisan Gerrymanders*, 14 Election L.J. 331 (2015); Jowei Chen, *The Impact of Political Geography on Wisconsin Redistricting: An Analysis of Wisconsin's Act 43 Assembly Districting Plan*, 16 Election L.J. (forthcoming 2017).

A number of courts have relied on computer simulations to assess partisan bias in maps. *See 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*, No. 1:15-CV-559, 2017 WL 1229736, at *6 (M.D.N.C. Apr. 3, 2017).

Just as mapmakers now have access to data analysis tools, statistics, and software to prepare biased and durable gerrymanders, courts now have access to a wealth of social science and technological tools to assist in classifying and identifying gerrymanders. These tools are new—they did not exist when the Court last considered these questions in *Vieth* and *LULAC*. These tools have been vetted by scholars, political scientists, and, in some cases, by courts, and are generally regarded as objective, verifiable, and reliable mechanisms to assess partisan bias. *See* Br. of Grofman & Gaddie 26-32. If the Court sets a doctrinal standard for partisan gerrymandering claims, there will be ample opportunity for lower courts to test the many viable tools that are now available and select the best social science evidence to identify constitutional violations.

CONCLUSION

For the foregoing reasons, *amici* respectfully urge the Court to affirm the judgment of the District Court.

Respectfully submitted,

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September 5, 2017

APPENDIX

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