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SUPREME COURT OF PENNSYLVANIA

No. 159 MM 2017

League of Women Voters of Pennsylvania, Carmen Febo San Miguel, James Solomon, John Greiner, John Capowski, Gretchen Brandt, Thomas Rentschler, Mary Elizabeth Lawn, Lisa Isaacs, Don Lancaster, Jordi Comas, Robert Smith, William Marx, Richard Mantell, Priscilla McNulty, Thomas Ulrich, Robert McKinstry, Mark Lichty, Lorraine Petrosky,
Petitioners,

v.

The Commonwealth of Pennsylvania; the Pennsylvania General Assembly, Thomas W. Wolf, In His Capacity as Governor of Pennsylvania; Michael J. Stack III, in His Capacity As Lieutenant Governor of Pennsylvania and President of the Pennsylvania Senate; Michael C. Turzai, In His Capacity As Speaker of the Pennsylvania House of Representatives; Joseph B. Scarnati III, In His Capacity As Pennsylvania Senate President Pro Tempore; Robert Torres, In His Capacity As Acting Secretary of the Commonwealth of Pennsylvania; Jonathan M. Marks, In His Capacity As Commissioner of the Bureau of Commissions, Elections, and Legislation of the Pennsylvania Department of State,
Respondents.

BRIEF OF AMICI CURIAE POLITICAL SCIENCE PROFESSORS IN SUPPORT OF PETITIONERS

On Consideration from the Commonwealth Court of Pennsylvania
Civ. No. 261 MD 2017

JORDAN B. YEAGER
Attorney ID No. 72947
CURTIN & HEEFNER, LLP
2005 S. Easton Road, Suite 100
Doylestown Commerce Center
Doylestown, PA 18901
(267) 898-0570
JBY@curtinheefner.com

ROBERT A. ATKINS*
NICHOLAS GROOMBRIDGE*
ANDREW J. EHRLICH*
PIETRO SIGNORACCI*
MICHAEL PERNICK*
PAUL, WEISS, RIFKIND, WHARTON & GARRISON LLP
1285 Avenue of the Americas
New York, NY 10019-6064
(212) 373-3000
ratkins@paulweiss.com
* Pro hac vice application pending.

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STATEMENT OF THE INTEREST OF *AMICI*[1]

Amici curiae are all nationally recognized university research scholars and political scientists from some of the foremost academic institutions in Pennsylvania and from across the country 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 A.

Amici have extensive professional knowledge and experience that will be relevant and helpful to the Court. *Amici* are among the leading scholars in Pennsylvania and across the country 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 in Pennsylvania.

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 in Pennsylvania.

[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.

Mapmakers have at their disposal more data—and more accurate data—about individual voters than ever before. Mapmakers have access to sophisticated 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 durable gerrymander to sort through a vast array of maps and select those that would entrench the most extreme partisan bias, all without violating previously established 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 across the country, including in Pennsylvania. 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 more biased and more durable than ever before.

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2 A "durable" gerrymander is one in which the gerrymandering party retains control of the legislature for multiple election cycles, with that control unlikely to be upset by the normal electoral process.

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 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). Like many maps across the country that emerged from this most recent round of redistricting, the congressional map in Pennsylvania has demonstrated extreme and durable bias in favor of one party. Laura Royden & Michael Li, Brennan Ctr. for Justice, *Extreme Maps* 1–2 (2017) (measuring the performance of Pennsylvania's congressional map over the 2012, 2014, and 2016 elections under three measures of partisan asymmetry); *see also* Recommended Findings of Fact ¶¶ 376, 385.

Mapmakers can intentionally engineer this kind of bias through the redistricting process 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 partisan bias, including Pennsylvania's redistricting process. Since then, the data and technologies available to draw such durable and biased districts have become much more precise and sophisticated.

A. Voter Behavior Is Predictable and Exploitable, Permitting Mapmakers to Create Intentionally Discriminatory Maps with Durable Partisan 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 voter data available to mapmakers 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, 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.[3]

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* 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. 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, 1589 (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

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[3] 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 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.

& Herbert F. Weisberg eds., 4th ed. 2001). These characteristics hold true among Pennsylvania voters. *See* Berwood Yost, *Disappearing Democrats: Rethinking Partisanship Within Pennsylvania's Electorate*, 12 Commonwealth 77, 84 (2003) (finding that partisan identity is an even stronger predictor of how Pennsylvanians voted in recent elections than party registration).

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 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." *See* Corwin D. Smidt, *Polarization and the Decline of the American Floating Voter*, 61 Am. J. Pol. Sci. 365, 365, 379–81 (2017). Tendencies among voters in Pennsylvania are consistent with the national trend: In Pennsylvania, there is a nearly perfect correlation in the level of support for candidates of the same party across elections. *See* Pet'rs' Post-Trial Proposed Findings of Fact ¶ 188. Given this correlation, it is easy to identify particular geographic units, down to the precinct level, that are likely to vote for candidates from a particular party. *Id.*

There also has been a measurable increase in the *intensity* of party preferences within the electorate, what is popularly referred to as "affective 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 (2015).

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.

One metric that coincides with this shift towards increased and stable partisanship is the well-documented decline of split-ticket voting.[4] 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 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. The decline in split-ticket voting coincides with a

[4] 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.

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, 7:04 AM), http://www.rollcall.com/news/hawkings/polarized-politics-split-tickets-midterms.[5]

Intervenors point to occasional instances of Pennsylvania districts changing party over two election cycles.[6] However, these isolated examples do not refute the increase in partisan voter behavior described above, and Intervenors make no attempt to show that they represent any underlying trend or even enduring feature of voter preferences. To the contrary, 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.

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5 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.

6 *See, e.g.*, Intervenors' Proposed Findings of Fact ¶ 54("Three counties that were won by President Obama in 2012 were won by President Trump in 2016 . . . ."); *id.* at ¶ 59 ("Thirteen counties in Pennsylvania had more registered Democrats than registered Republicans at the time of the 2016 presidential election but voted for President Trump."); Legislative Resp'ts' Proposed Findings of Fact and Conclusions of Law at 14 ("Voters who cast their ballots for Donald Trump in the Presidential election also cast their ballot for a Democrat for Congress.").

The concurrent phenomena of stable partisan identity as an indicator of voting preferences, intensifying partisanship, and the decline of ticket-splitting mean that mapmakers are able to rely on the predictability of voter behavior when working to maximize the partisan 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.[7] Political campaigns have always tried to predict the partisan affiliation of potential voters with data drawn from census information and their own volunteers, but in recent years, they have increasingly used advanced statistical models and predictive analytics. *See* David W. Nickerson & Todd Rogers, *Political Campaigns and Big Data*, 28 J. Econ. Persp. 51, 51, 59–61 (2014) (observing that, as recently as a decade or two ago, the techniques used by political campaigns "to predict the tendencies of citizens appear extremely rudimentary by current standards"). 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 at both the individual and

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

aggregate levels more accurately than ever.[8] This data includes, but is not limited to, census data, consumer data compiled and sold by businesses, voter information collected by political campaigns, political contribution history, precinct-level election results, and even analytic scores designed to predict voters' particular political characteristics. *See* Eitan D. Hersh, *Hacking the Electorate* 66, 69 (2015); 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 increase in available public data has coincided with the rise of detailed voter databases, referred to as "augmented voter files," which compile and curate voter data for use by political campaigns. *See* Hersh, *supra*, at 67. Augmented voter files contain traditional voter registration records that have been processed through data cleaning services and combined with substantial additional information. *Id.* 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 combination of

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[8] 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.

volunteered proprietary data and existing census and consumer data, funneled 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, 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 tailor durably biased maps. Users could quickly and easily develop redistricting plans based on customizable data sets, including data that predicts the projected partisan affiliation of voters. *See, e.g.*, AutoBound, https://citygategis.com/products/autobound (last visited Jan. 2, 2018).

Mapmakers aligned with both Republicans and Democrats used these techniques and technologies to craft maps in the most recent redistricting cycle. For example, in North Carolina, Maptitude was used to view past election data, color code the partisan voting history of each geographical unit, and assign such units to particular districts based on partisan data. *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). The maps that emerged from North Carolina's multiple rounds of redistricting this cycle, including court-ordered redistricting, have displayed substantial and durable partisan bias and consistently 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 2–4; Royden & Li, *supra*, 1, 6, 9 (2017); *Voter Statistics*, N.C. St. Board Elections & Ethics Enforcement, https://vt.ncsbe.gov/RegStat/Results/?date=12%2F29%2F2012 (last accessed Jan. 2, 2018).

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. *See* 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 4–7, *Benisek* v. *Lamone*, No. 13-cv-3233 (D. Md. May 31, 2017). 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 11–12, 27.

B. Pennsylvania's 2011 Congressional Map Is a Product of Partisan Gerrymandering Techniques

Pennsylvania's 2011 Plan was the product of similar techniques and technologies. After the 2010 election, the Republican redistricting teams in Pennsylvania—like many redistricting teams in the most recent cycle—prepared Pennsylvania's congressional maps using modern redistricting software that made extensive use of demographic and political data.

Pennsylvania's redistricting software, AutoBound, allowed its users to leverage "user-developed" data sets. *See* Transcript of Trial Day 3 PM Session at 84:18–20, 133:3–12, *Agre* v. *Wolf*, No. 17 Civ. 04392 (E.D. Pa. Dec. 13, 2017), ECF No. 197 (confirming that both the Senate and House staff used AutoBound); *see also AutoBound*, https://citygategis.com/products/autobound (last visited Jan. 2, 2018). In Pennsylvania, the user-developed data included 10 different indices that were not available from public sources, which assigned specific values to each precinct based on anticipated partisan performance. Pet'rs' Ex. 1 at 38–39; Tr. 301:13–309:5. The redistricting team computed these indices using extensive data for every precinct, municipality, and county in Pennsylvania for every statewide election, legislative election, and congressional election between 2004 and 2010. Pet'rs' Ex. 1 at 38.

Aided by the AutoBound program, the redistricting team compiled this information about partisan performance, which was reflected in precinct-level voting index scores, and presented it to various Republican stakeholders. Transcript of Trial Day 3 PM Session at 160:2–14, 163:2–8, *Agre*, No. 17 Civ. 04392. The redistricting team used this data to prepare at least a half-dozen maps that were presented to the Republican leadership, and fielded questions from Republican legislators about how the proposed districts would have performed in past elections. Transcript of Trial Day 3 PM Session at 79:25–80:7, 86:14–87:11, *Agre*, No. 17 Civ. 04392.

In 2012, under the maps that emerged from this process, Democrats won 50.8% of the two-party vote, yet won only 5 out of the 18 seats (27.8%) in Pennsylvania's congressional delegation. *See* Recommended Findings of Fact ¶¶ 183–84. Republican control has proven to be durable under these maps, as the Republicans have retained their majority in the subsequent years without a single congressional seat changing party hands. Although the Republican share of the two-party vote was 55.5% in 2014 and 54.1% in 2016, the party continued to control the same 13 seats (72.2%). *See* Recommended Findings of Fact ¶¶ 188–89, 194–95.

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

Recent innovations in data analytics used by businesses and scientific researchers can provide an 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. *Id.* at 869.

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

First, businesses and other entities have access to a greater amount of raw data about consumers. Corporations can either gather their own data, or purchase vast amounts of consumer information from "data broker" firms. *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-brokers-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, and credit agency reports, but they can also include nontraditional avenues of information such as consumer purchase histories and social media posts. *See* Fed. Trade Comm'n, *supra*, at 11–15; Richards & King, *supra*, at 404.

Second, in addition to having greater access to raw data, increased computing power[9] and new data analysis techniques allow businesses to predict increasingly subtle attributes of their consumers with even greater precision and 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). 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.[10]

In particular, the use of "machine learning" is particularly suited for analyzing complex data sets such as the behavior of individuals. "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

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9 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).

10 For example, Target concluded that a customer buying "cocoa-butter lotion, a purse large enough to double as a diaper bag, zinc and magnesium supplements and a bright blue rug" had an 87% chance of being pregnant. *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.

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.* 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.

B. <u>The Same Tools Employed in Business and Science Will Be Deployed to Create Partisan Gerrymandering Schemes That Appear to Comply with Traditional Redistricting Principles</u>

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 maps—all while satisfying historically-established 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. 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.

First, political data brokers or vendors are growing increasingly sophisticated in their ability to collect public voter information and create augmented voter files. Augmented voter files differ from older compilations of data because they are supplemented with more precise 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. *See* Hersh, *supra*, at 67.

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 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. However, basic regression techniques often struggle 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 nuances like this, past campaigns have had difficulty predicting individual voter behavior with accuracy. *See* Nickerson & Rogers, *supra*, at 59–61.

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 used to model political data will outperform standard procedures in terms of predictive accuracy and statistical reliability. *See* 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.

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.

A new theoretical technique called "matched-slice" gerrymandering can craft election maps in order to maximize partisan bias based on accurate, individualized knowledge of voter behavior. *See, e.g.*, Elmendorf, *supra*, at 43–44; 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, etc. Elmendorf, *supra*, at 43. 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. *Id.* 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*. at 44–45; *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 ward-level data of voter preferences. *See id.* at 44–45.[11] With the proliferation of individualized voter data, future mapmakers using the matched-slice technique will be able to maximize partisan bias and durability.

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[11] For example, a district may contain a simple 52% majority of voters siding with the party in control of the mapmaking process, but that majority may be composed of a mix of strong partisan voters and 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. 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.

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

Future gerrymanders could be designed to maximize partisan bias and durability while comporting with the traditional redistricting principles enumerated in the Pennsylvania Constitution.[12] Some states have already successfully crafted highly biased maps that do not appear, on their face, to violate these principles. Although many of the districts at issue in this case exhibit the bizarre shapes that are red flags of gerrymanders,[13] in future redistricting cycles, it will only become easier for mapmakers with access to advanced computing power to prepare thousands of simulated maps and identify the district configurations that can maximize partisan bias and durability while comporting with traditional districting principles.[14]

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 older redistricting cycles, gerrymanders had a self-limiting quality, because the gerrymandering party risked spreading its voting strength too

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[12] Under the Pennsylvania Constitution, state legislative districts must be "composed of compact and contiguous territory as nearly equal in population as practicable." Penn. Const. art. II, § 16.

[13] See Pet'rs' Post-Trial Proposed Findings of Fact ¶ 15.

[14] 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.

thin across too many districts. The more seats the gerrymandering party stacked in its favor, the more vulnerable that party would become in the event of a tide against that party. *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. The "newest, computer-driven redistricting now allows map drawers to make very precise refinements to district lines down to the census-block level." *See, e.g.*, Br. of Bernard Grofman and Ronald Keith Gaddie as Amici Curiae in Supp. of Neither Party at 17 n.5, *Gill* v. *Whitford*, No. 16–1161 (2017). 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.

With advances such as the augmented voter file and machine learning algorithms, aided by new techniques such as the matched-slice gerrymander, mapmakers are increasingly capable of forming districts that might appear to comport with traditional districting principles when they are in fact designed to entrench and expand partisan bias.

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 *Erfer* v. *Pennsylvania*, 794 A.2d 325 (2002), political scientists have developed a wealth of modern social science and computer modeling 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, 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.

The U.S. Supreme Court has adopted this approach in other redistricting contexts. In *Thornburg* v. *Gingles*, for example, the U.S. Supreme Court granted lower courts the flexibility to develop the doctrine of impermissible race-based redistricting. *See* 478 U.S. 30, 57–58 (1986). In *Gingles*, the U.S. Supreme 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 U.S. Supreme 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*. at 58.

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.*, *Whitford* v. *Gill*, 218 F. Supp. 3d 843, 884 (W.D. Wis. 2016) (finding an equal protection violation where a redistricting map reflected both a discriminatory purpose and a discriminatory effect); Pet'rs' Proposed Conclusions of Law ¶ 42 (proposing a similar inquiry under Pennsylvania equal protection law); Pet'rs' Proposed Conclusions of Law ¶¶ 18–19 (articulating a standard to evaluate content- and viewpoint-discrimination under Pennsylvania free expression law). 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 *Erfer*. In addition, these techniques are far more rigorous than and superior to historical approaches to identifying maps that were drawn with unconstitutional intent. 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—which calculates each party's "wasted" votes—is one metric that courts could utilize to detect partisan bias. *See* Nicholas O. Stephanopoulos & Eric M. McGhee, *Partisan Gerrymandering and the Efficiency Gap*, 82 U. Chi. L. Rev. 831, 834 (2015); *see also* Recommended Findings of Fact ¶ 369. A number of courts have already utilized the efficiency gap in order to assess partisan gerrymandering claims. *Whitford* v. *Gill*, 218 F. Supp. 3d 837, 898 (W.D. Wisc. 2016); *see also Common Cause* v. *Rucho*, 240 F. Supp. 3d 376, 380 (M.D.N.C. 2017).

Another social science test is the mean-median difference, which identifies when a party's median vote share is substantially below its mean vote share across districts in a state. When the median vote share is significantly lower than the mean, the party's voters are disproportionately located in packed districts. *See, e.g.*, Samuel S.-H. Wang, *Three Tests for Practical Evaluation of Partisan Gerrymandering*, 68 Stan. L. Rev. 1263, 1306–07 (2016); Br. of Grofman & Gaddie at 27, *Gill*, No. 16–1161 (2017); Recommended Findings of Fact ¶ 272.

B. Computer Simulations Provide Additional Tools to Assess Partisan Bias

Highly sophisticated computer modeling techniques can independently identify biased maps. Computer simulations 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, including those 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); 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); Br. of Political Geography Scholars as Amici Curiae in Supp. of Appellees, *Gill* v. *Whitford*, No. 16–1161 (2017).

A variant of these computer simulations is the Markov Chain technique, which involves making billions of small and randomized adjustments to a particular 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* (Mar. 15, 2017) (unpublished manuscript), http://imai.princeton.edu/research/files/redist.pdf; *see also* Recommended Findings of Fact ¶¶ 349–50. If the vast majority of those adjustments result in maps that exhibit a reduction in partisan bias when compared to the original map, they can support an expert conclusion that the original map is likely a partisan gerrymander.

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*, 251 F. Supp. 3d 935, 949 (M.D.N.C. 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 in the mid-2000s. 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. 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 request that the Court reject the Commonwealth Court's recommended conclusions of law and find in favor of Petitioners.

Respectfully submitted,

/s/ Jordan B. Yeager
JORDAN B. YEAGER
Attorney ID No. 72947
CURTIN & HEEFNER LLP
Doylestown Commerce Center
2005 S. Easton Road, Suite 100
Doylestown, PA 18901
(267) 898-0570
JBY@curtinheefner.com

ROBERT A. ATKINS*
NICHOLAS GROOMBRIDGE*
ANDREW J. EHRLICH*
PIETRO SIGNORACCI*
MICHAEL PERNICK*
PAUL, WEISS, RIFKIND, WHARTON & GARRISON LLP
1285 Avenue of the Americas
New York, NY 10019-6064
(212) 373-3000
ratkins@paulweiss.com
* Pro hac vice motion pending.

Attorneys for *Amici Curiae*[15]

January 5, 2018

[15] Melina Meneguin-Layerenza, Brittney C. Xu, and Jing Yan also contributed to the preparation of this brief.

APPENDIX A[16]

Professor Kevin Arceneaux is a professor of political science, director of the Behavioral Foundations Lab, and faculty affiliate in the Institute for Public Affairs at Temple University.

Professor Andrew Beveridge is a professor of sociology at Queens College and the Graduate Center at CUNY and CEO of Social Explorer.

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

Professor Bernard L. Fraga is an assistant professor of political science at Indiana University Bloomington.

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

Professor Lisa Handley is a Visiting Research Academic at Oxford Brookes University.

Professor Allison Harris is an assistant professor of political science at the Pennsylvania State University.

Professor Marie Hojnacki is an associate professor of political science at the Pennsylvania State University.

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16 Where provided, institutional affiliations are for informational purposes only and are not intended to indicate endorsement by the institution of the views of the individual amicus.

Professor Daniel Hopkins is an associate professor of political science at the University of Pennsylvania.

Professor Kristin Kanthak is an associate professor of political science at University of Pittsburgh.

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

Professor Yphtach Lelkes is an assistant professor of communication at the University of Pennsylvania.

Professor Marc Meredith is an associate professor of political science at the University of Pennsylvania.

Professor Clayton M. Nall is an assistant professor of political science at Stanford University.

Professor David Rohde is a professor of political science and Director of the Political Institutions and Public Choice Program at Duke University.

Professor Eric Schickler is a professor of political science at the University of California, Berkeley.

Professor Victoria Shineman is an assistant professor of political science at the University of Pittsburgh.

Professor Ariel White is an assistant professor of political science at the Massachusetts Institute of Technology.

Professor Ryan Vander Wielen is an associate professor of political science and (by courtesy) economics at Temple University.

Professor Jonathan Woon is an associate professor of political science and economics and director of the Center for the Study of American Politics and Society at the University of Pittsburgh.

Professor Christopher Zorn is the Liberal Arts Professor of political science and sociology at Pennsylvania State University.

CERTIFICATE OF COMPLIANCE

I, Jordan B. Yeager, Esq., certify that, based on the word count system used to prepare the foregoing Brief, that the foregoing Brief contains 6852 words, exclusive of the cover page, the Table of Contents, the Table of Citations, the signature block, and the certifications.

Date: January 5, 2018

/s/ Jordan B. Yeager

Jordan B. Yeager, Esq.
Pa. I.D. No. 72947
Curtin & Heefner LLP
2005 South Easton Road
Suite 100
Doylestown, PA 18901

SUPREME COURT OF PENNSYLVANIA

No. 159 MM 2017

League of Women Voters of Pennsylvania, Carmen Febo San Miguel, James Solomon, John Greiner, John Capowski, Gretchen Brandt, Thomas Rentschler, Mary Elizabeth Lawn, Lisa Isaacs, Don Lancaster, Jordi Comas, Robert Smith, William Marx, Richard Mantell, Priscilla McNulty, Thomas Ulrich, Robert McKinstry, Mark Lichty, Lorraine Petrosky,

Petitioners,

v.

The Commonwealth of Pennsylvania; the Pennsylvania General Assembly, Thomas W. Wolf, In His Capacity as Governor of Pennsylvania; Michael J. Stack III, in His Capacity As Lieutenant Governor of Pennsylvania and President of the Pennsylvania Senate; Michael C. Turzai, In His Capacity As Speaker of the Pennsylvania House of Representatives; Joseph B. Scarnati III, In His Capacity As Pennsylvania Senate President Pro Tempore; Robert Torres, In His Capacity As Acting Secretary of the Commonwealth of Pennsylvania; Jonathan M. Marks, In His Capacity As Commissioner of the Bureau of Commissions, Elections, and Legislation of the Pennsylvania Department of State,

Respondents.

CERTIFICATE OF SERVICE

I, the undersigned, certify that a true and correct copy of the foregoing Brief of Amici Curiae Political Science Professors In Support of Petitioners was served upon all counsel of record, via electronic service, on this date.

Date: January 5, 2018

/s/ Jordan B. Yeager

Jordan B. Yeager, Esq.
Pa. I.D. No. 72947
Curtin & Heefner LLP
2005 South Easton Road
Suite 100
Doylestown, PA 18901