ELECTION LAW JOURNAL
Volume 00, Number 0, 2021

DOI: 10.1089/elj.2020.0691

A Measure of Partisan Advantage in Redistricting

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ABSTRACT

I propose a new measure of partisan advantage in redistricting. This measure compares the observed seat outcome in each state to a seat benchmark based on the state's jurisdictional map. The jurisdictional seat benchmark for a party is proportional to the share of the population in jurisdictions (counties and towns) won by this party. This jurisdictional benchmark takes into account the state's political geography and is simple to compute. I define a party's Jurisdictional Partisan Advantage as the difference between the seats the party obtains in an election and the seats that correspond to this party according to the jurisdictional benchmark. Using U.S. election data from 2012 to 2020, I find a Jurisdictional Partisan Advantage of 17 House seats to the Republican party. I argue that the Jurisdictional Partisan Advantage in the congressional maps of North Carolina, Utah, and Ohio during the 2011–2020 redistricting cycle was excessive.

Keywords: redistricting, political gerrymandering, partisan fairness, partisan advantage

1. INTRODUCTION

"PARTISAN GERRYMANDERING'' is the practice of drawing electoral districts to favor a political party. The U.S. Supreme Court (SCOTUS) has found that partisan gerrymandering is "incompatible with democratic principles."[1] However, in 2019 SCOTUS also found that "none of the proposed tests for evaluating partisan gerrymandering claims meets the need for a limited and precise standard that is judicially discernible and manageable,"[2] and finding no manageable standard to measure partisan gerrymandering, it declared the problem nonjusticiable in federal courts.

Two normative axioms help to explain why SCOTUS has repeatedly refused to accept any proposed measure of partisan fairness.[3] A redistricting map satisfies "partisan symmetry" if all parties translate votes into seats equally well under this map; for instance, if each of two parties gets half the vote, they each get half the seats, and if one party needs 55% of the vote to obtain k seats, then any other party also needs 55% of the vote to obtain k seats. Whereas, a redistricting map satisfies "neutrality" if it delivers the same seat outcomes as a neutral

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I thank A. Tybl, A. Earle, and especially Christian Cox for diligent research assistance, and John Curiel for extensive discussions and valuable ideas. I am also grateful to C. Ahlin, S. Ansolabehere, J. Chen, M. Duchin, J. Katz, G. King, A. Miller, C. Smidt, N. Stephanopoulos, three anonymous reviewers, participants at the 2019 PECA conference in Chicago, the Big 10 Alliance's SPARK conference in College Park, an Institute for Public Policy Social Research (IPPSR) public forum on redistricting in Lansing (Michigan), and participants at seminars at Michigan State University, New York University, and Harvard University for their comments. I completed an earlier draft while employed as a visiting associate professor of government at Harvard University. I gratefully acknowledge IPPSR for funding through a Michigan Applied Public Policy Research grant. I note that I volunteered for the organization Voters Not Politicians, which led the 2018 successful campaign for constitutional reform of redistricting in Michigan.

[1] Opinion of the Court in *Rucho v. Common Cause*, 139 S. Ct. 2484, 2506 (2019).
[2] Quoting from the Syllabus, *Rucho v. Common Cause*, 139 S. Ct. 2484, 2489 (2019).
[3] In *Davis v. Bandemer*, 478 U.S. 109 (1986); *Vieth v. Jubelirer*, 541 U.S. 267 (2004); *League of United Latin American Citizens (LULAC) v. Perry*, 548 U.S. 399 (2006); and finally, in *Rucho v. Common Cause*, No. 18-422, 588 U.S. ___ (2019).

baseline obtained from maps drawn exclusively to follow traditional redistricting criteria and without any partisan considerations (Grofman 2018).[4] If the geographic distribution of partisan supporters is asymmetric—as it happens, for instance, if one party's supporters are more heavily clustered in cities—then maps that satisfy neutrality will not satisfy symmetry.

The prevailing academic measures on partisan fairness quantify deviations from symmetry.[5] In fact, some authors emphatically identify redistricting fairness with symmetry (Katz, King, and Rosenblatt 2020; Cervas and Grofman 2020). Crucially, a (conservative) majority of SCOTUS justices does not: SCOTUS has determined that "asymmetry alone is not a reliable measure of unconstitutional partisanship,"[6] that the asymmetries that arise when "a legislature draws district lines with no objectives in mind except compactness and respect for the lines of political subdivisions" are "natural,"[7] and that attempting to reverse them to turn a neutral map into a symmetric one constitutes "reverse gerrymandering."[8]

While partisan gerrymandering claims will now be disputed in state legislatures and in state courts according to state law, SCOTUS's understanding of fairness and its relation to neutrality remain relevant insofar as it is shared by state jurists. Thus, motivated by SCOTUS's enumeration of desiderata for a measure of partisan fairness, I propose a simple and manageable measure of deviations from neutrality in redistricting maps.

The measure I propose is rooted in the electoral system under the 1776 Pennsylvania Constitution, at the origins of American democracy. Under this constitution, each representative in the Pennsylvania General Assembly represented either a county or the city of Philadelphia, with the number of legislators representing each jurisdiction set to be "in proportion to the number of taxable inhabitants" (1776 Penn. Const. § 17). The seat outcome we would obtain under this electoral system is a neutral seat benchmark based on the state's jurisdictional map. The difference between the seats that a party obtains under a given map of single-member districts and the seats it would obtain in this neutral jurisdictional benchmark is a precise and simple measure of the partisan advantage that a party obtains through the redistricting process. I refer to this measure of the deviation from the jurisdictional benchmark as the "Jurisdictional Partisan Advantage."

The jurisdictional map I use to create the neutral benchmark in each state is the map with jurisdictional units—counties, cities, or townships—closest in population size to the population represented by one seat in the assembly.[9] Apportioning seats—or voting weights—to the party that wins the popular vote in each fixed jurisdiction satisfies the "one-person, one-vote" principle of equal representation (*Reynolds* v. *Sims* 1964) by assigning seats to each jurisdiction in proportion to its population.[10] Since the proportional apportionment is unique, the seat outcome given a voting profile is also unique, and thus the benchmark is neutral by construction.

In contrast, redistricting satisfies the "one-person, one-vote" principle by redrawing district boundaries to equate population across districts. However, since there are very many different ways to draw equal population districts, and since different maps deliver different seat outcomes, some maps favor one political party over others. Congress first mandated single-member districts (ruling out the apportionment method) for federal elections in 1842. Apportioning seats to multi-member districts with fixed jurisdictional boundaries remains possible for state legislatures. For instance, New Hampshire uses this system for elections to its House of Representatives: "When the population of any town or ward, according to the last federal census, is within a reasonable deviation from the ideal

[4]Traditional nonpartisan redistricting principles include population equality, respect for the Voting Rights Act, contiguity, respect for jurisdictional boundaries, and compactness of districts.

[5]Including Partisan Bias (Tufte 1973), the γ-measure (Nagle and Ramsay 2021), the efficiency gap (Stephanopoulos and McGhee 2015), the median-mean difference (McDonald and Best 2015), and the declination (Warrington 2018). I discuss these measures in Section 5.

[6]Opinion of the Court in *LULAC v. Perry*, 548 U.S. 399, 420 (2006).

[7]Justice Scalia's Plurality Opinion in *Vieth v. Jubelirer*, 541 U.S. 267, 290 (2004).

[8]Opinion of the Court in *Rucho v Common Cause*, 139 S. Ct. 2484, 2501 (2019).

[9]In Pennsylvania, these jurisdictional units are the counties and the city of Philadelphia; in most other states, they are the counties.

[10]The U.S. Electoral College, and the qualified majority rule in the European Council, follow approximately this method.

population for one or more representative seats, the town or ward shall have its own district of one or more representative seats" (N.H Const. art. XI).[11]

The normative underpinning of the jurisdictional benchmark is that the congressional choice to require single-member districts, which prompted the need to redistrict, should preserve the balance of political power that would materialize were states to return to the historical precedent of apportioning seats to jurisdictions. Any seats obtained with a given redistricting map in excess of those that would accrue to a party under the neutral apportionment method constitute a partisan advantage in redistricting.

I next review the judicial background on partisan gerrymandering, and I discuss how the measure of Jurisdictional Partisan Advantage can be used in light of these precedents, in Section 2. In Section 3 I define the measure and how to compute it; in Section 4 I show results for the 2012–2020 redistricting cycle, with Supplementary Tables; and in Section 5 I discuss alternative ways to measure partisan fairness. I relegate to a Supplementary Appendix a state-by-state detailed discussion, for selected states of greatest interest, and an extensive discussion of caveats and limitations of the measure I propose.

2. JUDICIAL BACKGROUND, AND USES OF THE MEASURE OF PARTISAN ADVANTAGE

Partisan gerrymandering distorts political representation and policy outcomes (see, for instance, Stephanopoulos 2017–2018 and Caughey, Tausanovitch, and Warshaw 2017). As I mentioned above, in *Rucho* (2019), SCOTUS declared it "incompatible with democratic principles." However, it also ruled that claims of partisan gerrymander are not justiciable under federal law. In finding that partisan gerrymandering claims cannot be addressed or adjudicated in federal courts, SCOTUS reversed the precedent set in *Davis v. Bandemer* (1986) and followed in *Vieth* (2004) and in *LULAC* (2006); it directly overturned lower court rulings against the North Carolina and Maryland congressional maps; and it indirectly voided similar lower court rulings against the congressional maps in Ohio and Michigan, and against the legislative maps in Wisconsin.[12]

In the opinion of the court in *Rucho*, SCOTUS explains that any standard for evaluating whether a map is a partisan gerrymander "must be grounded in a limited and precise rationale and be clear and politically neutral."[13] In *Vieth*, a majority of justices had sought a standard that is "easily administrable."[14] Finding none, SCOTUS concludes that partisan gerrymandering claims are not judiciable in federal courts. SCOTUS concedes that: "Excessive partisanship in districting leads to results that reasonably seem unjust," and it argues that SCOTUS "does not condone excessive partisan gerrymandering."[15] Rather, SCOTUS finds a solution in state courts: "Provisions in state statutes and state constitutions can provide standards and guidance for state courts to apply."[16]

Indeed, most states protect voting rights more explicitly than the U.S. Constitution does (Douglas 2014). Fifteen states have explicit provisions on partisan fairness in their state code.[17] Others have "equal and free" or "equal" election clauses. State courts in Florida, Pennsylvania, and North Carolina have seized on these protections to adjudicate partisan gerrymandering claims.

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[11]Towns that do not reach the threshold for a seat merge with others to form a district. In addition, New Hampshire forms a second layer of so-called "floterial" districts, superimposed on the jurisdictional ones. These additional districts aim to provide representation proportional to the population in excess of the threshold for the number of seats in the town's district. For instance, under the 2011 map, two legislators represent the town of Belmont (pop. 7,356), four legislators represent the adjacent city of Laconia (pop. 15,951), and since Belmont and Laconia together have enough population (23,307 inhabitants) for seven seats, together they elect a seventh representative that represents both towns.

[12]The cases are *Whitford v. Gill*, 218 F. Supp. 3d 837 (W.D. Wis. 2016), in Wisconsin; *Common Cause v. Rucho*, 279 F. Supp. 3d 587 (M.D.N.C. 2018), in North Carolina; *Benisek v. Lamone*, 348 F. Supp. 3d 493 (D. Md. 2018), in Maryland; *League of Women Voters v. Benson*, No. 2: 17-cv-14148 (E.D. Mich. Apr. 25, 2019), in Michigan; and *Phillip Randolph Institute v. Householder*, No. 1: 18-cv-357 (S.D. Ohio May 3, 2019), in Ohio.

[13]Opinion of the Court in *Rucho v. Common Cause*, 139 S. Ct. 2484, 2498 (2019).

[14]*Vieth v. Jubelirer*, 541 U.S. 267, 290, and 310 (2004).

[15]Opinion of the Court in *Rucho v. Common Cause*, 139 S. Ct. 2484, 2506–2507 (2019).

[16]Opinion of the Court in *Rucho v. Common Cause*, 139 S. Ct. 2484, 2507 (2019).

[17]I provide a summary of these provisions in Supplementary Table S1.

TABLE 1. PARTY VOTE SHARE BY ISLAND IN EXAMPLE 1

	Left Island	*Center Island*	*Right Island*	*Total*
Party A	90%	30%	30%	50%
Party B	10%	70%	70%	50%

In 2015, Florida's Supreme Court struck down the state's 2011 congressional map as a violation of the "Fair Districts" clause in the state's constitution. This clause says that no district shall be drawn "with the intent to favor or disfavor a political party."[18] The court later adopted a remedial map, which was then used in the 2016, 2018, and 2020 elections.[19]

In 2018, in *League of Women Voters v. Commonwealth* (hereafter, LWV18), Pennsylvania's Supreme Court struck down the state's 2011 congressional map as a partisan gerrymander in violation of the Pennsylvania Constitution, which states that "elections shall be free and equal."[20] A remedial map drawn by a court-appointed master was used in the 2018 and 2020 elections.

In 2019, North Carolina's Wake County Superior Court struck down the state's legislative maps, finding them a partisan gerrymander in violation of the North Carolina Constitution, which mandates that "elections shall be free."[21] The legislature drew remedial maps for 2020, which the court approved.[22]

These three court cases in Florida, in Pennsylvania, and in North Carolina show how partisan gerrymandering claims will follow different paths in different states. In Florida, the court's decision revolved about evidence of partisan intent, befitting the letter of Florida's "Fair Districts" clause. Quantitative measures of partisan fairness—including the Jurisdictional Partisan Advantage—measure outcomes, not intent. These measures are thus better suited to evaluate violations of clauses that prohibit partisan outcomes. For instance, the Michigan Constitution explicitly states that whether a map is unacceptably partisan "shall be determined using accepted measures of partisan fairness."[23]

A question arises: Which measures of fairness? The question is best divided into two parts: Which concept of fairness do we want to measure? And, given a concept, how do we quantify it? On the concept of partisan fairness, let us revisit the distinction between "symmetry" and "neutrality" through a stylized example.

Example 1. A state composed of three islands with equal population, named Left I., Center I., and Right I., holds elections to a three-seat legislature, and obtains the election results in Table 1.

If both parties obtain equal statewide vote share, symmetry requires that parties obtain in expectation an equal number of seats (one seat each and one coin toss over the third, or three coin tosses). But the political geography in Example 1 favors Party B: voters are sorted in such a way that if each island elects its own representative, Party A wins one seat, and Party B wins two. To attain symmetry, we would need to draw (to gerrymander?) cross-island districts in favor of Party A. Neutrality requires instead that the seat outcome be the one we obtain if we design the electoral system without any partisan consideration; in Example 1, representation by island means that Party B gets two seats.

A strong case for symmetry can be made.[24] Missouri embraces it in its constitution (Mo. Const. art. III, § 3). But SCOTUS rejected it in *LULAC* (2006),[25] and then more explicitly in *Rucho* (2019): SCOTUS observed that any claim that a map is unfair "because it makes it too difficult for one party to translate statewide support into seats [...] is based on a norm that does not exist in our electoral system" (2499). Instead, in the two state court rulings against partisan maps in Pennsylvania and North Carolina, the courts found that these

[18] *League of Women Voters of Florida v. Detzner*, 172 So.3d 363 (Fla. July 9, 2015), and Fla. Const. art. III, § 20(a) and § 21(a).

[19] *League of Women Voters of Florida v. Detzner*, 179 So.3d 258 (Fla. Dec. 2, 2015).

[20] *League of Women Voters v. Commonwealth*, 178 A.3d 737 (Pa. 2018) (hereafter LWV18); Pa. Const. art. I, § 5.

[21] *Common Cause v. Lewis*, 358 F. Supp. 3d 505 (D.N.C. 2019), and N.C. Const. art. I, § 10.

[22] After the same court issued an injunction against the state's 2016 congressional map in *Harper v. Lewis*, No. 5:19-CV-452-FL (E.D.N.C. Oct. 22, 2019), the legislature also drew a new congressional remedial map, which was used in the 2020 election. The 2016 congressional map was itself a remedial map drawn to replace the 2011 congressional map struck down as a racial gerrymander in *Harris v McCrory,* 159 F. Supp. 3d 600, (M.D.N.C. Feb. 16, 2016).

[23] Mich. Const. art. IV. § 6. In fact, the idea for the measure of Jurisdictional Partisan Advantage originated in discussions around the text of this clause, when it was part of a ballot initiative, before this initiative was adopted as an amendment to the Michigan Constitution in 2018.

[24] See footnote 5 and following text, and Section 5.1 devoted to measures of partisan symmetry.

[25] See Opinion of the Court in *LULAC v. Perry*, 548 U.S. 399, 420 (2006).

maps violated traditional nonpartisan redistricting criteria, and that they reduced a party's representation below the number of seats the party would have obtained under nonpartisan maps that complied with such criteria—i.e., the courts found that the maps violated neutrality. Further, the Pennsylvania court went on to adopt an "almost perfectly neutral"—but not symmetric—remedial map (Cervas and Grofman 2020).

As discussed by Grofman and Cervas (2018), and Cervas and Grofman (2020)—and implicitly, by the Pennsylvania Supreme Court—LWV18 (n.71) serves as a template for partisan gerrymandering cases in other states with similar election protection clauses. I highlight three features of this ruling. One: it struck down a map based on its properties and the outcomes it generated, regardless of intent. Two: evidence on statewide aggregate outcomes sufficed to condemn the map, without need to demonstrate harm to voters in a specific district. And three: evidence that the map leads to partisan outcomes was obtained by comparing the seat outcome under the challenged map to a neutral baseline. In LWV18, the neutral baseline was derived from an ensemble of computer-simulated maps. The Democratic Party obtained fewer seats under the challenged map than under almost any map in the ensemble. The state court in North Carolina also embraced this approach (*Common Cause* v. *Lewis* 2019), as did the dissent in *Rucho* (2019, 2518), which suggested as a measure of partisan distortion the deviation in seats from the neutral baseline defined by the median seat outcome among all maps in the ensemble.

Given their proven success in court, ensemble methods are the most salient tool to challenge future partisan gerrymanders by showing evidence of their statewide partisan effects.[26] However, note that both in LWV18 in Pennsylvania, and in the North Carolina case, the evidence from ensembles persuaded Democratic jurists, which constituted a majority in these courts.[27] Notably, in the 5–2 decision in LWV18, both Republican justices dissented. If any plaintiffs seek judicial relief from partisan gerrymandering in courts without Democratic majorities, these plaintiffs will need to persuade some conservative jurists. The following questions are then relevant: What is the conservative critique to the existing measures of partisan fairness? How would conservative jurists measure partisan fairness?

In his dissent in LWV18, Chief Justice Saylor tells us that his state court "would benefit from anticipated guidance from the Supreme Court of the United States" (831), and that if his court's process were sufficiently deliberative, he "would proceed to sift through the array of potential standards to determine if there was one which I could conclude would be judicially manageable" (834). Guidance from SCOTUS arrived in the opinion in *Rucho.* While SCOTUS dismissed all measures of partisan fairness for use as a federal standard (rejecting, inter alia, the measures based on ensemble methods), it invited state courts to be the ones to adjudicate partisan gerrymandering claims. To do so, state courts will need a standard. If such standard is based on a quantitative measure, SCOTUS' conservative majority has articulated a list of desiderata that the measure should satisfy. It should be simple ("clear," "precise," "limited," "manageable," "discernible"),[28] it should accept the natural asymmetries that arise due to political geography, it should rely on actual voting patterns (not on counterfactual ones),[29] it should accept that parties are not entitled to any representation based on their statewide vote-share, and it should be "politically neutral."[30]

The measure of Jurisdictional Partisan Advantage satisfies all these desiderata. It is, by design, a tool tailored to quantify partisan advantage in redistricting according to SCOTUS' specifications. That is, as preferred by Chief Justice Saylor above, it follows SCOTUS' guidance.[31]

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[26]I discuss ensemble methods at length in Section 5.2.

[27]All five justices in the majority in LWV18 won their seats running as Democrats in partisan elections. In the North Carolina case, one of three judges won the office as a Democrat, while two won theirs in nonpartisan elections, and two of the three registered as Democrats. All four SCOTUS justices in the dissent in *Rucho* were nominated by Democratic presidents.

[28]Opinion of the Court in *Rucho v. Common Cause*, 139 S. Ct. 2484, 2498 (2019).

[29]Opinion of the Court in *LULAC v. Perry*, 548 U.S. 399, 420 (2006).

[30]Opinion of the Court in *Rucho v. Common Cause*, 139 S. Ct. 2484, 2498–2499 (2019).

[31]By this I mean that the measure does not originate with the author's own notion of what constitutes fair representation. Unlike, say, Cervas and Grofman (2020), or Katz, King, and Rosenblatt (2020), who advocate for fairness as they understand it, I propose a measure of partisan advantage as I think the conservative majority in SCOTUS (and in other courts) understands the term. It is their understanding of fairness and partisan advantage that is relevant, not mine, so I propose a tool designed to fit their views.

While the measure of Jurisdictional Partisan Advantage is most closely related to the outlier tests in ensemble methods, it has one advantage over these methods—and in some states, it has two.

An advantage is that Jurisdictional Partisan Advantage is simpler. It relies on a fixed jurisdictional map to obtain a unique neutral baseline number of seats, and this baseline is easy to compute, using election data by jurisdiction that for most states is widely available. Whereas, the ensemble approach defines neutrality with respect to a large sample of simulated maps (an ensemble), and the computational methods to generate this ensemble are complex, while the properties of the sample are difficult for a lay audience to understand.[32] Further, for most elections, the results by precinct required by the ensemble method are not easily available.[33]

In some Eastern states, the jurisdictional benchmark has a second strength as a neutral baseline. Namely, the jurisdictional benchmark has historic roots at the origins of American democracy: "Representation in the colonies was uniformly based on geographic units, whether towns, counties or parishes," with more populous jurisdictions often obtaining more delegates (Squire 2013). The founding fathers articulated that an ideal district must "preserve natural political communities, as institutionalized through the functional design of towns and counties" (Curiel and Steelman 2018). Indeed, at the time of the U.S. Constitutional Convention in 1787, the units of representation for the lower houses in 12 of 13 states in the Union were the county or the town (Kromkowski 2002, Table 5.6; Pole 1966). The jurisdictional benchmark is the neutral seat outcome we would have obtained if we had preserved these original units of representation, and we abided by the equal population requirement (*Reynolds* v. *Sims* 1964) by weighing each such jurisdictional unit by population.

For instance, the "free and equal" election clause in the Pennsylvania Code dates from its 1790 Constitution (art. IX § V). As the framers of this constitution declared that elections shall be free and equal, they also determined that representation to Pennsylvania's House of Representatives would be by jurisdiction (each county, and the city of Philadelphia), with representation to each jurisdiction in proportion to its population, as in the jurisdictional benchmark. One infers that the framers deemed the jurisdictional benchmark fair, and jurists who value original intent may weigh this inference as they assess the benchmark.[34] Subsequent institutional changes to mandate single-member districts—with the concomitant opportunity to draw and redraw their boundaries—were influenced by partisan motivations[35] and brought additional partisan distortions into the electoral system.[36] The outcome under the electoral system that preceded these partisan distortions stands out as a salient notion of a neutral baseline … in Eastern states along the Atlantic seaboard.[37]

In summary, the jurisdictional benchmark identifies a neutral seat baseline based on a fixed map of jurisdictions, weighed by population.[38] The Jurisdictional Partisan Advantage measures deviations from this neutral benchmark. It does not propose a judicial standard for identifying partisan gerrymanders. A standard would include not only a measure of partisan gain, but also a determination as to how much partisan gain is tolerable and how much is too much. I propose only a measure, leaving up to the

[32]Underscoring this difficulty, the Opinion of the Court in *Rucho* (2019) mischaracterizes the ensemble method, before dismissing it. The ensemble method does not "line up all the possible maps drawn [a State's own districting] criteria according to the partisan distribution they would produce" (2505). Rather, an ensemble lines up a non-representative sample. The difference is important, and taking only a non-representative sample is arguably for the better (DeFord, Duchin and Solomon 2020).

[33]The ensemble method has advantages too. Notably, it demonstrates what is possible, and it proposes maps one could use that satisfy desired constraints. Whereas, the jurisdictional benchmark provides only a baseline outcome, without suggesting how to draw neutral maps.

[34]Similarly, the clause that elections in North Carolina shall be "free" dates to its 1776 Constitution, which also stipulated that these elections to the state Senate shall be by county, and those to the state House, by county and by one of six prominent towns (art. II and III).

[35]For example, congressional legislation to require single-member districts in federal elections was passed in 1842 to favor the Whig party in Congress (Engstrom 2013; *Rucho v. Common Cause*, 139 S. Ct. 2484, 2499 (2019)).

[36]Partisan distortions are such an integral part of redistricting that scholars such as Dixon (1968) argue that redistricting inevitably entails gerrymandering.

[37]As we move west to states of more recent creation, this argument appealing to original intent loses its force, because such states never experienced representation by counties and towns.

[38]Historically, the creation of counties and delimitation of their boundaries was an endogenous process, subject to partisan motivations (Branning 1960). However, once formed, county boundaries are more stable. In modern times, these boundaries are fixed over the horizon of one redistricting cycle and are thus not subject to partisan manipulation.

courts in each state to determine how much is too much.[39] Nevertheless, since the measure is comparable across cases, it allows us to draw inferences from precedent: for instance, any congressional map of Pennsylvania that favors a party as much as the one struck down in LWV18 would seem suspect of being an unconstitutional gerrymander as well. Further, I derive a measure of advantage relative to the size of the delegation (the "Excess Advantage") that is comparable across states. Should any future map exhibit a relative advantage of magnitude as great as the worst in the 2012–20 cycle, such map would have to contend with quantifiable charges that its deviation from a neutral jurisdictional baseline is extreme.

The neutral jurisdictional baseline, and the one based on large ensembles of simulated maps can be used together to reinforce each other, rather than in substitution of each other. Even advocates of partisan symmetry—as long as they believe that the perfect should not be the enemy of the good—may want to measure deviations from neutrality: since neutral maps are typically not too far from symmetry, if courts are amenable to striking maps that are far from neutral, eliminating these maps would leave us with maps that are closer to symmetry.

The Jurisdictional Partisan Advantage measure can also help mapmakers attempting to draw fair maps. In principle, a redistricting commissioner or legislator interested in drawing a fair map needs to first answer a normative question: What does it mean for a map to be "fair"? should it satisfy partisan symmetry? Should it satisfy neutrality? In practice, a mapmaker may embrace a normative stance inclusive of both axioms, deeming a map fair if it deviates from neutrality only insofar as the deviations bring the map closer to partisan symmetry. And once again, because maps that satisfy neutrality are typically not far from satisfying symmetry, mapmakers can draw a map that performs relatively well on both criteria. A pragmatic mapmaker may wish to compute many measures of fairness, including the Jurisdictional Partisan Advantage, for any proposed plan. Ideally, the selected map will perform well according to all measures; if it performs well in some and poorly in others, we can use this information to evaluate the merits of the plan, and if it performs poorly in the measures deemed more compelling by the mapmaker, the map should be redrawn.

I next formally define the measure of Jurisdictional Partisan Advantage.

3. DEFINITION OF THE PARTISAN ADVANTAGE MEASURE

Consider a state S and an assembly A in which state S has a delegation of k seats. Consider a redistricting map m that partitions state S into k districts with approximately equal population. Consider a voting profile v, which indicates how each citizen voted in an election in state S. For each party p that competes in state S, let $s_p(v,m)$ denote the number of seats that party p wins, given the voting profile v and the redistricting map m.

Given the voting profile v and a benchmark number of seats $s_p(v)$ for party p, I define the *Partisan Advantage* that map m gives to party p relative to benchmark $s_p(v)$, as

$$s_p(v,m) - s_p(v).$$

The benchmark $s_p(v)$ I use is a *jurisdictional benchmark* based on the state's jurisdictional map. A question arises: Which jurisdictional map? Are the most appropriate jurisdictions the counties, or are they subcounty divisions such as cities and townships? Historically, the answer varied by state. In most states, the preeminent political subunit is the county. Communities were represented by county in colonial and early state assemblies in mid-Atlantic and early Southern states (Kromkowski 2002). In most of the Union, counties were designed to delineate local political communities, typically with a county seat (and a county court) near its center. County boundaries were meant to be such that the county seat could be reached within a day of travel by wagon from any settlement in the county, in order to allow all citizens to assemble in political activities at the county seat (Hamilton, Madison, and Jay 1787; Stephan 1971), and to strengthen the link between representatives and their constituents (Curiel and Steelman 2018).

[39]What social scientists can do, and what I do, is "to provide the analytic framework and metrics that courts can draw upon to draw standards" (Grofman and Cervas 2018). Jurists can then gradually develop standards through the accumulation of cases and precedents on either side of a threshold for admissibility of a map (see footnote 11 in Grofman and Cervas 2018).

Table 2. Jurisdictional Benchmark in New Hampshire, 2020

County name	*[1] Pop*	*[2] D Vote*	*[3] R Vote*	*Pop. counties won by* *[4] Dem*	*[5] Rep*
Belknap	60,088	16,228	20,487	0	60,088
Carroll	47,818	15,909	16,082	0	47,818
Cheshire	77,117	25,323	16,690	77,117	0
Coos	33,055	8,014	7,761	33,055	0
Grafton	89,118	32,359	19,215	89,118	0
Hillsborough	400,721	118,879	101,732	400,721	0
Merrimack	146,445	48,476	37,595	146,445	0
Rockingham	295,223	95,664	94,276	295,223	0
Strafford	123,143	40,617	29,396	123,143	0
Sullivan	43,742	12,426	10,811	43,742	0
N. HAMPSHIRE	*1,316,470*	*413,895*	*354,045*	*1,208,564*	*107,906*
				91.80%	8.20%
	Jurisdictional benchmark			1.84	0.16

However, in Western states, of more recent settlement, this tight association of counties with local political communities weakens or disappears altogether: Maricopa County, for instance, is larger than four of the original 13 states in both area and population, and it contains more than half the population of Arizona.[40] And in New England states, since colonial times the preeminent local jurisdiction has been the township, not the county.

Given this heterogeneity across states, I adopt a unifying axiomatic approach to choose the relevant jurisdictional map uniformly across all states: I use the jurisdictional units closest in population size to the districts that need to be drawn.

Congressional districts in the 2012–2020 election cycle represented approximately 710,000 residents each. Across all states—with few exceptions discussed below—the jurisdictional unit closest in population size to 710,000 inhabitants is the county. Hence, in most states, the jurisdictional map I use is the state's county map. For each county, I credit the total county population to the party that wins the popular vote in the county; aggregating across counties, the jurisdictional benchmark $s_p(v)$ is proportional to the total population in counties in which party p won the popular vote. Table 2 demonstrates this procedure to compute the jurisdictional benchmark in New Hampshire.

For each county, column [1] in Table 2 indicates the population of the county; column [2] is the popular vote for the Democratic Party in the county, aggregated across all races for U.S. House seats in the county; column [3] is the analogous popular vote for the Republican Party in the county. In counties in which the Democratic Party candidates got more votes ([2] > [3]), the population of the county is assigned to the Democratic column [4], whereas if the Republican Party got more votes ([3] > [2]), the county population goes to the Republican column [5]. Adding up across counties, we get the state totals. We find that 91.8% of the population is in counties won by the Democratic candidates. Since New Hampshire has two congressional districts, the number of Democratic Party seats according to the jurisdictional benchmark is 91.8% of two seats, that is, 1.84 seats.[41]

County population varies greatly across counties.[42] Most counties are much smaller than a congressional district; whereas, a few are much larger. To draw maps of equal-population electoral districts in redistricting maps, several small counties must be grouped together. However, since there is no substate jurisdictional level larger than the county, and no simple, unique way to group independent counties,[43] I treat small counties—however

[40] San Bernardino County in California has area greater than seven of the 13 original states, and, according to the 2010 U.S. Census, Los Angeles County (also in California) had population greater than all but eight states in the Union.

[41] Data sources: 2010 U.S. Census (column [1]) and New Hampshire Secretary of State (columns [2] and [3]). Columns [4] and [5] are computed from the first three columns.

[42] From only 90 inhabitants in Kalawao County (Hawaii), to close to ten million in Los Angeles County (California), according to the 2010 U.S. Census.

[43] See Duque, Ramos, and Suriñach (2007) for a survey of computational approaches to aggregate a set of areas into a predefined number of spatially contiguous regions, and Duque, Anselin, and Rey (2012) for an approach that endogenizes the optimal number of regions.

small—as independent units in the construction of the jurisdictional benchmark, as in New Hampshire in Table 2.

On the other hand, counties that are too large can be split by subcounty jurisdictions such as cities and townships. I split counties with population size greater than a threshold equal to the population of two average districts. For the 2012–2020 congressional redistricting cycle, this threshold is approximately 1,415,000 inhabitants.

Subject to fixing a unique threshold across all states, this population threshold to split a county is the lowest possible one that guarantees that the population of each subcounty unit I consider is closer than the population of the county as a whole, to the population of an average district.[44]

Out of the 2,844 counties in the 42 states in which I measure the Jurisdictional Partisan Advantage, only 23 have population above this threshold. In these large counties, there could be two subcounty jurisdictions larger than a district, and such that a different party wins in each of these subjurisdictions. Crediting the whole county to the county-wide majority party would hide this large minority. Wherever possible, I correct this problem by splitting these large counties into smaller jurisdictional units, by iteratively taking out their largest cities or townships and treating them as independent jurisdictions, until the population in the remainder of the county is less than 1,415,000 inhabitants. Supplementary Table S2 lists the resulting collection of jurisdictional units after splitting the largest counties in this manner.[45]

Formally, given this set of jurisdictional units U in state S, for each jurisdictional unit u in U in state S, let n_u denote the population in u, and let n be the total population in the state. For each party p, each district d and each jurisdictional unit u in U, let $v_p(u,d)$ be total number of votes that party p obtains in the precincts of district d that lie within unit u. Party p wins in unit u if its sum of votes across all precincts in unit u is the greatest, that is, if $\sum_d v_p(u,d) > \sum_d v_{p'}(u,d)$ for any other party p'.[46]

Then I calculate the jurisdictional benchmark number of seats $s_p(v)$ by assigning $\frac{n_u}{n}k$ seats to party p for each jurisdictional unit u in U in which party p won the popular vote given the election results v, where k is the total number of seats to assign.

This procedure can be summarized by the following definition of Jurisdictional Partisan Advantage.

Definition 1. Given a partition of a state into the jurisdictions closest in size to the districts to be drawn, the Jurisdictional Partisan Advantage *conferred by a redistricting map to a given party is the difference between the seats the party obtains and the seats that correspond to the party in proportion to the total population of the collection of jurisdictions in which the party won the popular vote.*

Or, in short, the Jurisdictional Partisan Advantage is the difference between the seats that a party obtains and the party's jurisdictional benchmark number of seats.

A note on nomenclature: in previous versions, I referred to the Jurisdictional Partisan Advantage as "Artificial" Partisan Advantage. In their implementation and use of this measure, the team at the online redistricting tool DRA 2020 use the term "Boundary Bias" to refer to the Jurisdictional Partisan Advantage divided by the total number of seats in the state.[47] The term "Jurisdictional Partisan Advantage" references that this definition measures the deviation with respect to a "jurisdictional" benchmark number of seats that is based on the state's jurisdictional map. Thereafter, I use the short-hand term "Partisan Advantage" to refer to the Jurisdictional Partisan Advantage as introduced in Definition 1.

While choosing the jurisdictions closest in size to the districts to be drawn best aligns the level of aggregation in the benchmark to the one in the actual electoral maps, as a robustness check, we can also compute variants of the Partisan Advantage using coarser or finer partitions of the state into larger or smaller jurisdictions. I pursue these robustness checks, computing the resulting measure for all states using only counties (with no splits); using

[44]During the 2012–2020 redistricting cycle, the average district population was just under 710,000 inhabitants.

[45]I split 19 large counties into cities and townships: Alameda, Los Angeles, Orange, Riverside, Sacramento, San Bernardino, San Diego, and Santa Clara in California; Bexar, Dallas, Harris, and Tarrant in Texas; Maricopa in Arizona, Cook in Illinois; Middlesex in Massachusetts; Wayne in Michigan; Clark in Nevada; Suffolk in New York, and King in Washington. The four large counties that cannot be split into cities or townships are Kings, New York, and Queens (because they are themselves boroughs within the City of New York), and Philadelphia, because the city and the county coincide.

[46]Ties are unlikely, and rare. If a tie occurs, I assign half the population of the unit to each party.

[47]DRA 2020 is a free web app to create, view, analyze, and share redistricting maps for all 50 states. It is available at <davesredistricting.org> (Bradlee 2020).

subcounty units only for counties with population greater than that of three, four, or five congressional districts; and, for the states and elections for which the data is readily available, aggregating by townships or by precincts.[48]

In addition to a set of jurisdictional units (U), to compute the jurisdictional benchmark we also need a voting profile (v). There are two decisions to make about the voting profile. The first is whether to use results from elections to the seats for which we are defining the benchmark (so-called "endogenous" election data), or to use results from other ("exogenous") elections. The second decision is whether to use the exact election results to assign seats, or to subject the results to some statistical treatment, introducing some smoothing function to attenuate the effect of chance in winning a district or a jurisdictional unit only by a handful of votes.

The most appropriate choices on the input data depend on whether we want to use the jurisdictional benchmark to evaluate redistricting maps retrospectively (what happened in past elections?) or prospectively (what is likely to happen in future elections?). Section 4 is devoted to the retrospective evaluation of the 2012–2020 congressional maps. For such a retrospective evaluation, I second Cervas and Grofman (2020): "the best evidence about a plan's partisan consequences is, of course, evidence derived from actual elections under the plan." Therefore, I use endogenous results from 2012–2020 U.S. House elections. And, to keep the measure simple and transparent to a lay audience unfamiliar with statistical methods, I use the exact election results. I relegate to robustness checks all additional results with data from other elections or with smoothing statistical functions.

Whereas, for a prospective evaluation of maps conducted before the endogenous elections are held—for instance, while evaluating a proposed map for possible adoption—we must use data from exogenous elections. For a prospective evaluation, while computing the jurisdictional benchmark remains a simple task, we also need to predict a seat outcome under the new map. To compute this outcome, we need predicted results by precinct, and the choice of exogenous election is then limited by data availability (this is the same data constraint faced by the ensemble methods for any kind of evaluation, whether prospective or retrospective). Further, for a prospective evaluation, a probabilistic prediction as to how the map is likely to perform in the future is more informative than an exact computation as to how it would perform if an exogenous election result were to be exactly repeated. Thus, to evaluate a new map based on expectations over its future performance, I would suggest assigning seats to each party according to a continuous function of past vote shares, as in the robustness checks and in much of the literature.

4. DATA AND RESULTS

I compute the Partisan Advantage in the 2012–2020 elections to the U.S. House of Representatives. There are 43 states that draw district maps, because they have at least two delegates. From these I exclude Florida because it does not hold elections for uncontested races, so it does not provide the data about the winners' support necessary to compute the measure. For the 2018 and 2020 elections I exclude Maine as well, because in 2018 it changed its electoral rule to Alternative Vote. Therefore, I compute the Partisan Advantage for 42 states for the 2012, 2014, and 2016 elections, and for 41 states for the 2018 and 2020 elections.

Population data by jurisdiction is publicly available from the 2010 U.S. Census. Election results data is publicly available from each state's Secretary of State. I use election results from the 2012–2020 elections to the U.S. House of Representatives for the main analysis and in some robustness checks, and results from the 2012 and 2016 U.S. presidential elections in other robustness checks.[49]

[48]As I report in the Supplementary Appendix, if we use the county maps exclusively, without county splits, results for 2012–2020 congressional maps are similar in California and Illinois (the states with the largest counties), and identical or near identical in all other states. In fact, the main results (the aggregate Partisan Advantage, and the states with the greatest advantage) are qualitatively robust across levels of granularity in the jurisdiction map used to construct the benchmark. Taking these robustness checks to the limit, the smallest level of aggregation is at the individual level (no aggregation at all), and corresponds to a proportional representation benchmark; whereas, the highest level of aggregation, at the state level, corresponds to a winner-takes-all seat allocation.

[49]I use the original, publicly available data from each state clerk's office for the 2018 election, and for all years for states with a top-two primary (California, Washington, and Louisiana). For convenience, for the 2012, 2014, 2016, and 2020 elections in all other 39 states, I use the compilation by county available from Dave Leip's Atlas of U.S. Presidential Elections (2021). Data by subcounty jurisdictions are always from each county's clerk's office.

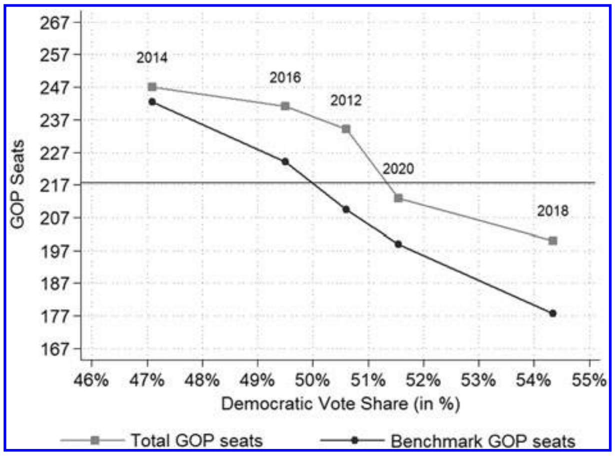

FIG. 1. GOP jurisdictional benchmark and total seats as a function of the Dem. vote share.

On aggregate across all states, and on average across all five elections, the *Partisan Advantage* is *17 seats* for the Republican Party. Disaggregating by election, but still aggregating across all states, the Partisan Advantage for the Republican Party was 25 seats in 2012, 5 in 2014, 17 in 2016, 22 in 2018, and 14 in 2020.[50]

Figure 1 compares the actual number of Republican seats in the House of Congress as a function of the Democratic vote share to the total number of Republican seats if in the states in the sample we substitute the number of Republican seats according to the jurisdictional benchmark for the actual Republican seats. The aggregate Partisan Advantage is the difference between these two magnitudes. The horizontal line, at 217.5 seats, is the threshold above which a party attains majority status in the House.

For an election in which the Republican Party wins the vote share by a large margin (such as in 2014), there is very little Partisan Advantage. The advantage materializes only as the electoral returns of the Republican Party deteriorate: as the Democratic vote share increases from 47% to just over 50%, many counties flip, but very few districts do so, and the gap between the number of seats won by Republicans and the number of seats according to the jurisdictional benchmark widens. The "swing ratio" or "responsiveness" (Tufte 1973)[51] of the Republican jurisdictional benchmark with respect to the Democratic vote share from the 2014 result (47% Democratic) to the 2012 result (50.6% Democratic) is −2.16. But the responsiveness of actual Republican seats with respect to Democratic vote share is only −0.85.

The consequence is that under the 2011 redistricting maps, elections in which the Republican Party wins the national popular vote by a little (as in 2016) or loses it by a little (as in 2012), deliver a seat outcome similar to the one if the Republican Party wins by a lot (as in 2014).

We may wonder: How much of the partisan bias in favor of the GOP is due to natural factors such as the geographic sorting of voters, and how much is due to the way redistricting maps were drawn? To answer this question, I compute the Partisan Bias (the deviation from symmetry) of the (neutral) jurisdictional benchmark. If the popular vote in an election is tied, the population in jurisdictional units won by each party will not be tied, so the jurisdictional benchmark will assign more seats to one party than to the other. This is the Partisan Bias of the jurisdictional benchmark in a tied election, which we can interpret as the portion of the total bias that is due to political geography, and not to redistricting.

I construct a hybrid election, composite of the 2012 and 2016 elections, such that in this synthetic election, the two-party, 42-state vote share is tied.[52] In this synthetic tied election, the jurisdictional benchmark assigns 203.3 seats to the GOP, and 197.7 to the Democratic Party, out of the 401 seats in these 42 states. Thus, the GOP earns according to the benchmark 2.8 additional seats, relative to an even split. In contrast, according to the maps in use, in this synthetic tied election the seat outcome would be a 220–181 majority for the GOP; that is, the GOP would obtain 19.5 more than an even split. Since only 2.8 seats of this seat gain also appear under the jurisdictional benchmark, the difference of 16.7 seats is not due to political geography; rather, it is an advantage introduced by the redistricting process. Therefore, I estimate that approximately 86% of the seat gain at a tied election (or

[50]The sharp decrease in the Republican Partisan Advantage from 2012 to 2014 is discussed by Goedert (2015). The decline in 2020 is in part because by then, three of the maps that had yielded a greatest advantage to the GOP (the maps in Virginia, Pennsylvania, and North Carolina) had been struck down by federal and state courts. The remedial maps reduced the GOP advantage by about five seats.

[51]The "swing ratio" or "responsiveness" is defined as the percentage change in seats corresponding to a change of one percent in vote share.

[52]I obtain this hypothetical election result with a tied vote share by multiplying the 2012 vote totals by 0.15, multiplying the 2016 vote totals by 0.85, and adding up.

Partisan Bias) that favors the GOP is an advantage obtained through drawing biased redistricting maps, with only 14% due to political geography.

Alternatively, we can consider a counterfactual in which the election is tied in each state.[53] For the 41 states with results in all five elections,[54] and on average across all these five elections, the GOP would obtain a gain of 19.7 seats over an even split under the actual maps, but a gain of only 3.0 seats under the jurisdictional benchmark, for a difference of 16.7 seats, so once again 85% of the seat gain is driven by the redistricting maps, and only about 15% of this advantage is due to political geography.

I compare these results to Royden and Li (2017). They use several measures of deviations from symmetry, and election results from 2012, 2014, and 2016 to evaluate the partisan fairness of 26 states with at least six congressional seats. They conclude that "Republicans derive a net benefit of at least 16-17 congressional seats." They note that "residential sorting almost certainly does contribute to partisan bias," but they conjecture that this sorting is "unlikely" to explain the worst biases, a conjecture shared with McGann et al. (2016). On the other hand, Chen and Cottrell (2016) argue that geographic sorting explains most of the bias. Chen and Cottrell (2016) explain that they use a large collection of simulated maps as a neutral benchmark because we lack a baseline of "the outcomes that would have resulted in the absence of gerrymandering."[55] The jurisdictional benchmark provides this missing baseline: it is the outcome that would have resulted without redistricting, and thus the deviation in seat outcomes from the jurisdictional benchmark under a given redistricting map measures the partisan gain due to redistricting. Vindicating Royden and Li (2017) and McGann et al. (2016), I find that Partisan Advantage in redistricting, and not political geography, explains most of the Partisan Bias in 2011 congressional maps.[56]

While these aggregate patterns are indicative of the magnitude of the Partisan Advantage, redistricting is conducted independently by each state, and for evidence of partisan gerrymandering we must look at each state independently.

In Supplementary Tables S3–S7 I show the Partisan Advantage in each election from 2012 to 2020 for each state. These tables report for each state: the size of the state's delegation; the fraction of the two-party vote obtained by the Republican Party; the total population in jurisdictions won by each party; the number of seats that accrue to the Republican Party according to the jurisdictional benchmark; the number of seats that the Republican Party actually won; and in the last column, the Partisan Advantage as the difference between the preceding two columns (negative numbers correspond to a Partisan Advantage for the Democratic Party).[57]

Because the absolute magnitude of the Partisan Advantage correlates with the size of the state's delegation, I compare the results across states using a notion of *Excess Advantage* that is relative to the size of each state's delegation. Since the jurisdictional benchmark is a fractional seat allocation, and actual seat outcomes are integers, it follows that the smallest possible Partisan Advantage is the difference between the benchmark and the nearest integer, which can be as large as 0.5 seats. Therefore, I allow a rounding margin of 0.5 seats, and I define the Excess Advantage as the Partisan Advantage in excess of this rounding margin, divided by the size of the state's delegation.

Definition 2. The Excess Advantage *is* $\frac{\textit{Partisan Advantage}-0.5}{\textit{state's delegation size}}$ *if the Partisan Advantage is over 0.5 seats, and zero otherwise.*

Averaging across all five elections, the encouraging finding is that 18 states feature zero Excess Advantage. Other states have an Excess Advantage, typically favoring the party that controlled the map-drawing. Figure 2 illustrates the distribution of

[53]For each House election from 2012 to 2020, and for each state, I construct an associated hypothetical election with vote share tied at the state level. I obtain this hypothetical tied vote share by proportional shift, as in Nagle (2015 or 2019), multiplying the returns of a party in each jurisdiction by a common factor. As stated in Nagle and Ramsay (2021): "Although a proportional shift […] is conceptually superior to the commonly used uniform shift, the difference between the two is not consequential […]."

[54]Recall Maine drops out of my analysis after it adopted the Alternative Vote electoral system.

[55]I discuss Chen and Cottrell (2016) and the related literature on computationally generated ensembles of maps in Section 5.2.

[56]In related work, Eubank and Rodden (2020) estimate the bias that arises from political geography directly, by computing each party's "spatial efficiency." This spatial efficiency is defined as the fraction of voters for whom the circular neighborhood centered around the voter would be competitive if it were a district. They show that both spatial efficiency and control of the redistricting process result in greater seat shares, which implies that political geography explains some, but not all, of the total partisan bias in seat outcomes.

[57]As shown in Supplementary Table S8, the measures of Partisan Advantage for the individual states are highly correlated across elections.

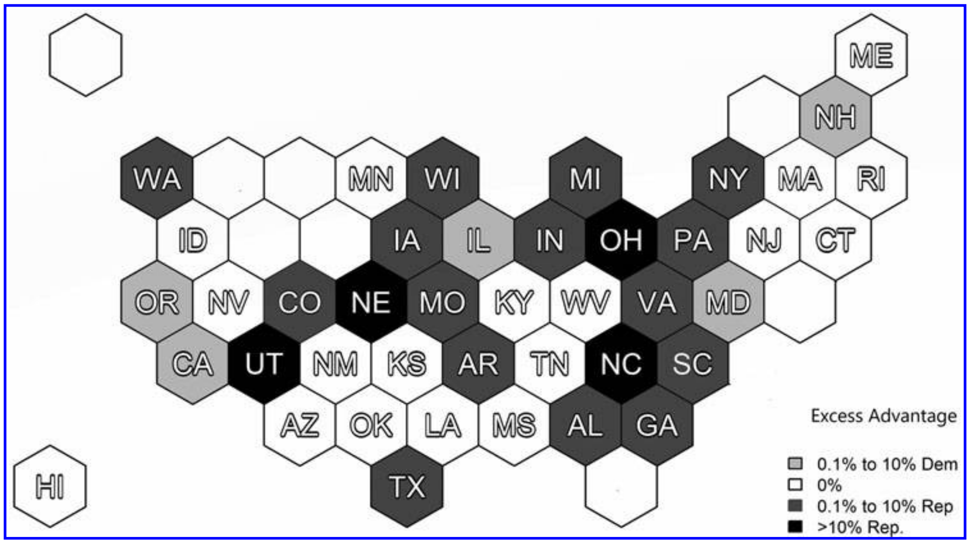

FIG. 2. Excess Advantage across 42 states, 2012–2020.

results across the states: states with maps that provide an Excess Advantage to the GOP are in dark gray (or in black if the Excess Advantage surpasses 10%); states with maps that favor the Democratic party are in lighter gray; and states with neutral maps in white.[58]

I highlight the most extreme maps in Table 3, noting their Partisan Advantage and the size of their state's delegation. In Supplementary Table S9 I provide the Partisan Advantage and the Excess Advantage for each state.

As a robustness check, I also compute the measure of Partisan Advantage using the election results from the 2012 and 2016 U.S. presidential elections (in each jurisdiction and in each congressional district), instead of the results in the elections to the U.S. House of Representatives. I drop Illinois and Utah, home states of the Democratic and Republican 2012 presidential candidates, because the home-state bias in voting makes the vote in the presidential election not a meaningful proxy for a hypothetical House election. On the other hand, I can add Florida, which was contested by both presidential candidates.

The aggregate result across the 40 states included in both methods (all but Florida, Illinois, and Utah) is similar using 2012 election data: 28 seats of Partisan Advantage for the GOP using the House election results, and 29 seats using the presidential election results. Using 2016 election data, the Partisan Advantage for the GOP is greater with the presidential election results: 26 seats instead of 17. State by state, there is a strong correlation between the average Partisan Advantage computed using results from the two presidential elections or from the two U.S. House ones for 2012 and 2016: the Pearson correlation coefficient is greater than 0.89. The states with greatest Excess Advantage are North Carolina, Ohio, Michigan, and Pennsylvania. North Carolina, Ohio, and Michigan feature an Excess Average Advantage greater than 15% using either pair of election results; Pennsylvania shows an 18% Excess Average Advantage using the presidential election results, and 10% using the congressional ones.[59] Notably, Nebraska drops out of the list of worst maps, showing a more modest Excess Advantage (5%) when computed with the presidential election results. I report the Partisan Advantage and the Excess Advantage in each state using the 2012 and 2016 presidential election results in Supplementary Table S10.

As an additional robustness check, I consider a smoothed version of the jurisdictional benchmark. In this version, I treat 2012–2020 U.S. House election results as indicative of the probability that the party would win a given district or jurisdiction in another U.S. House election, on the premise that a party that won by only a few votes would be

[58]Hexagons in white with no state initial represent states that have only one district, or, in the case of Florida, do not run uncontested races.

[59]Recall this 2012–2016 congressional map of Pennsylvania was struck down in LWV18.

Table 3. States with Greatest Excess Advantage, 2012–2020

Excess Advantage, and size	*Partisan Advantage*	*Democratic Advantage*	*Republican Advantage*	*Partisan Advantage*	*Excess Advantage, and size*
			North Carolina '16–'18	3.20	20.7% of 13
			North Carolina '12–'18	2.87	18.2% of 13
			Utah	1.15	16.2% of 4
			Nebraska	0.84	11.3% of 14
			Ohio	2.14	10.3% of 16
8.7% of 8	1.19	Maryland			

In 2016–2018 North Carolina used a remedial map based on its 2012–2014 map. In 2020 it used a very different remedial map.

much less likely to win again than one that won by a landslide. Instead of assigning each jurisdiction's weight to the benchmark of the party that wins most votes (in a winner-take-all fashion), I use a continuous assignment function with a parameter value d: party p earns no seats for the benchmark from jurisdiction j if p obtains vote share below $0.5 - d$ in jurisdiction j, but for vote shares in between $0.5 - d$ and $0.5 + d$, it earns seats for the benchmark in linear proportion to its vote share.[60] Finally, if the party gets vote share of at least $0.5 + d$, it earns all the seats apportioned to the jurisdiction. Similarly, for the observed seat outcomes under the assigned map, I also compute this smoothed outcome, so if a party barely won a seat by a handful of votes, this seat counts as little more than half a seat (because the party is far from certain of being able to retain it in future elections). I then compare this smoothed outcome to the smoothed benchmark, for different values of d.

I report the results for $d = 0.01$ in Supplementary Table S11.[61] These results are robust, both in the nationwide aggregate, election by election and on average over all five elections, and in each state except Nebraska. In Nebraska—as in the presidential elections robustness check—the GOP's Excess Advantage is halved in the smoothed version. This indicates that the extreme Excess Advantage in Nebraska in the exact computation of the measure was in part due to how very close results panned out.[62]

DRA 2020 provides a related robustness check, with a smoother assignment of seats. For a given set of elections used as input data, they compute the mean vote share in each relevant geographic unit (a district or a jurisdiction). They assume that election results in each unit are drawn from a distribution with mean equal to the unit's observed mean vote share (as in Nagle 2019, or Nagle and Ramsay 2021). In this manner, they estimate the probability that a party wins any given unit. They also estimate the expected seats that a party will win, which they call "map seats," and the expectation over the jurisdictional benchmark number of seats, which they call "geographic seats." The difference between the expected seats and the geographic seats is their expectation over the Partisan Advantage. They refer to this expectation, divided by the total number of seats, as the "boundary bias." I report the results of this robustness check, using results from the 2012 and 2016 presidential elections, for 33 states, in Supplementary Table S12.[63] Notice that the expectations of the Excess Advantage across states (in Supplementary Table S12) as computed by DRA 2020 using these two presidential elections are

[60]For instance, it gets a quarter of the jurisdiction's seats for vote share 0.5-d/2, half for vote share 0.5, and three quarters for 0.5 + d/2.

[61]Note d = 0.01 means that a party gets credit for a close loss if it loses the vote share by less than 2%. Results with thresholds to start assigning credit at 4%, 8%, 12%, 16% and 20% are available from the author.

[62]Indeed, in 2020, the GOP lost two Nebraska counties (Douglas and Lancaster) worth 1.3 seats by a 0.5% vote share difference. The exact benchmark assigns the party zero seats for these losses; the smoothed one assigns it 0.48 seats. In a state with only three seats to assign in each election, this difference alone suffices to lower the Excess Average Advantage over the entire cycle by 3.2%, reclassifying Nebraska out of the tier of greatest Partisan Advantage (with North Carolina, Utah, and Ohio), and into a tier of Excess Advantage between 5% to 10% (with Arkansas and Michigan for the GOP, and Illinois and Maryland for the Democratic Party).

[63]At the time of creating Supplementary Table S12 (June 2021), DRA 2020 was working on the code to compute the measure for subcounty jurisdictions, so Supplementary Table S12 includes only the states for which the relevant jurisdictional map is the county map. Further, as in Supplementary Table S10, I exclude Illinois and Utah. As of July 2021, at DRA 2020's website (Bradlee 2020), any reader is able to compute the expected Partisan Advantage in every state, using a wider selection of election results as input.

similar to the smoothed values of the Excess Advantage using all five U.S. House elections, as shown in Supplementary Table S11.[64]

Notice that the maps of North Carolina and Ohio are identified as extreme partisan gerrymanders under every specification.

5. COMPARISON TO OTHER MEASURES OF PARTISAN FAIRNESS

I first review, in subsection 5.1, measures of partisan fairness that quantify some asymmetry or difference in how parties translate votes or vote shares to seats, regardless of the source of the difference. These measures, including the Partisan Bias; local and global partisan symmetry; linearity in responsiveness; the efficiency gap; the median-mean difference; and the declination, are measures of total advantage for a party.

The measure of Partisan Advantage is, instead, a measure of deviations from neutrality, which quantifies the net partisan advantage, net of the so-called "natural" (Cervas and Grofman 2020),[65] "unintentional" (Chen and Rodden 2013; McDonnald and Best 2015), or "accidental" (Erikson 1972) advantage due to a state's political geography.

I discuss a growing literature on measuring deviations from neutrality through ensemble methods in subsection 5.2. The "outlier test" or "ensemble" approach is based on computationally generating a large ensemble of redistricting maps, so that we can compare the properties of the enacted map against the distribution obtained from the ensemble. The Partisan Advantage is most closely related to this approach.

5.1. Measures of partisan fairness that capture deviations from symmetry

Several measures of partisan fairness in redistricting measure asymmetries in how parties convert votes to seats. For each of two main parties *A* and *B* (holding constant the votes for minority parties), we construct the party's "vote-to-seats" curve by mapping the number of seats that the party obtains if it gets fraction x of the statewide two-party vote, for each x between 0 and 1. The notion of "Partisan Bias" is a pointwise measure: the Partisan Bias in favor of *A at vote share x* is the difference between the number of seats that Party *A* obtains if it gets a fraction x of the two-party vote, and the number of seats that Party *B* obtains if *B* gets fraction x of this vote (Butler 1951 and 1952). From the pointwise measure, we can obtain a global axiom: "partisan symmetry" holds if the Partisan Bias is zero for any vote share x, so that the two vote-to-seats curves are equal (Tufte 1973; Grofman 1983; King and Browning 1987).

Given a probability measure over possible two-party vote shares, we can integrate the difference between the two vote-to-seat curves weighed by this probability measure. The resulting measure of global Partisan Bias is the expectation over the pointwise bias (Katz, King, and Rosenblatt 2020). Partisan Bias is the most prominent notion of partisan fairness in the academic literature.[66]

Partisan symmetry only requires that both parties share a common vote-to-seats curve, without additional constraints on the properties of this curve. In unbalanced states in which one party is confident that it will obtain a vote share in the interval [v,V] with $0.5 < v < V$, and that the event of obtaining vote share no greater than $1 - v$ is implausible, this freedom can be exploited to draw maps that respect partisan symmetry, but are such that a vote share between v and V suffices to win a large number of seats—or perhaps all seats.

To rule out such possibility, some recent measures of fairness introduce additional constraints beyond symmetry. The "γ" measure (Nagle and Ramsay 2021) is based on the idea that fairness requires the vote-to-seats curve to be linear. To compute the measure, we first compute the responsiveness (the slope) of the votes-to-seats curve at an expected vote share, and we draw a hypothetical linear vote-to-seats curve with this slope that respects partisan symmetry. The local "γ" measure is the deviation of the actual vote-to-seats curve from this linear curve deemed fair, at the expected vote share. The efficiency gap (McGhee 2014; Stephanopoulos and McGhee 2015 and 2018)—in the

[64]In particular, large results in Oregon, Pennsylvania, and Georgia in the robustness check in Supplementary Table S10 that diverged from results using House elections (Supplementary Table S11) appear to be the result of chance. Some noise is expected using the exact outcomes of only two elections; once outcomes are smoothed out, results using House and presidential elections are more aligned.

[65]Also, Opinion of the Court in *Rucho v Common Cause* 139 S. Ct. 2484, 2501 (2019).

[66]See, for instance, influential work by Cox and Katz (1999) or Grofman and King (2007), among others.

simpler case with equal turnout across districts—requires that the vote-to-seats curve be linear with slope equal to two.[67]

Other measures rely instead on the rank-vote curve, which plots the vote shares obtained by a party in each district, ranked from lowest to highest. The "median-mean" difference is the difference between the vote share in the median district and the mean vote share in the state, (McDonald and Best 2015). One may think that this difference should be zero (Edgeworth 1898), but it is not zero if, for instance, one party wins large landslides in cities and another wins smaller majorities in rural and suburban areas (Butler 1951 and 1952; Erikson 1972).[68] Gerrymandering affects the median-mean difference because changing the composition of districts can change the vote share in the median district, but leaves the mean vote share unchanged.

The "declination" (Warrington 2018 and 2019) considers not just the median district, but the entire rank-vote curve, to measure whether there is a discontinuity in the distribution of results at districts on either side of the 50% vote share threshold. This discontinuity would appear anomalous if districts were naturally drawn, but it will happen by design if districts are gerrymandered.[69]

All these measures capture asymmetries in how parties translate votes to seats. However, if the geographic distribution of voters is itself asymmetric, violations of partisan symmetry are not necessarily indicative of a map's partisanship. In the words of SCOTUS, because "the existence or degree of asymmetry may in large part depend on conjecture about where possible vote-switchers will reside" […] "asymmetry alone is not a reliable measure of unconstitutional partisanship" (*LULAC* v. *Perry* 2006, 420).

Recall that in the three-island Example 1 in Section 2, if each island constitutes its own district, Party A wins one district, and Party B wins two. The Partisan Bias is then large, as are the deviation from partisan symmetry, the γ-measure of nonlinearity, the efficiency gap, the median-mean difference, and the declination. The large asymmetry in this example is not due to a partisan drawing of election districts, but due to the sorting of voters across the three islands. Political geography in this archipelago favors Party B: if a district map respects the neutral principle of respecting island boundaries, then Party B wins two districts and Party A only one, despite a tied vote share.

In the next subsection I discuss the ensemble approach to construct a neutral baseline and to quantify deviations from it. The Partisan Advantage based on the jurisdictional benchmark contributes most directly to this literature.

5.2. *Measures of partisan fairness that capture deviations from neutrality*

The prevailing approach to capture the effect of political geography on seat outcomes—and to measure biases net of this effect—is to computationally generate a large ensemble of maps and to study the distribution of outcomes under the maps in this large ensemble. This distribution serves as a neutral baseline: if we compare the outcome under the enacted map against this distribution, we can determine whether the enacted map is an outlier. Since political geography affects the baseline, the difference between the seat outcome under the enacted map and the median seat outcome in the ensemble is a measure of the partisan bias net of the effect of political geography. That is, this method measures deviations from neutrality in seat outcomes.

The quickly expanding literature on the ensemble approach includes Chen and Rodden (2013 and 2015); Chen and Cottrell (2016); Cho and Liu (2016); Cho (2019); DeFord and Duchin (2019); Chin, Herschlag, and Mattingly (2019); and Chen and Stephanopoulos (2021), among others.

This method is compelling, but it presents formidable technical challenges. First, it is difficult to define the set of admissible maps from which to draw maps for the ensemble. Say we determine that in order to be admissible, maps ought to be somewhat compact: How compact?[70] Or, if admissible maps ought to comply with the Voting Rights Act (VRA), then the determination of whether a map

[67]In general, and accounting for unequal turnout, the efficiency gap is the difference in the share of wasted votes for each party, where wasted votes are those cast for a losing candidate, or for a winning candidate in excess of 50% +1. This measure has elicited criticism (Chambers, Miller, and Sobel 2017; Bernstein and Duchin 2017; Katz, King, and Rosenblatt 2020; Rush 2020).
[68]On the urban/rural divide and its effects on redistricting, see as well Rodden (2019).
[69]See Wang (2016) as well for other tests of symmetry in the distribution of votes across districts, and Grofman (2019) for a review of recent advances in this literature.
[70]On compactness, see Chambers and Miller (2010) and Saxon (2020).

complies with the Act is a step that is hard to automate. Once we overcome (or put aside) this difficulty, and we settle on a set of admissible maps, a second challenge emerges: it is difficult to devise a random algorithm to draw a sample from the set of admissible maps.[71]

Since the neutral baseline under this approach is defined by an ensemble of maps, understanding the properties of this ensemble is paramount to interpret any deviation from the baseline. Alas, for many map-generating algorithms used in this literature, the properties of the ensemble are unknown.

For instance, in pioneering work, Chen and Rodden (2013) create an ensemble with 100 congressional maps of Florida, using an algorithm that merges precincts and swaps them across districts until it reaches a valid district map. They use 2000 presidential election results in Florida to compare the enacted 2011 congressional map to this ensemble. They find that the seat outcome under the enacted map (17 GOP seats out of 25) gives one more seat to the GOP than the median number of seats under the maps in the ensemble, but the enacted map is not an outlier.[72] Chen and Rodden (2015) conduct a similar exercise to evaluate 24 of the 27 districts in the 2011 Florida congressional map, this time generating 1,000 maps. Using the 2008 presidential election results, this time they find the map is an extreme outlier: the GOP obtains three additional seats under the enacted map, relative to the mode, median, and mean of the ensemble.[73] Chen and Cottrell (2016) extend the analysis nationwide, generating an ensemble with 200 maps for each state. They find that the difference between the GOP seat share under the enacted plan and the median of the distribution of GOP seat outcomes in the ensemble is greater than 5% in favor of the GOP in Utah, North Carolina, and Ohio. However, they also find a difference greater than 5% favoring the Democratic party in the maps of Louisiana and Alabama—both drawn by GOP legislatures—and in the maps of Arizona (drawn by an independent commission), so on aggregate the GOP obtains a minimal gain of one seat nationwide.[74]

Cho and Liu (2016) use a different algorithm (Liu, Cho, and Wang 2016) to generate 258,000 maps of Maryland to evaluate the state's 2011 congressional maps. They find that in 21% of these maps, the Democratic Party would obtain seven seats, as in the enacted plan (so the enacted plan is not a statistical outlier). The net gain for the Democratic Party with the enacted map relative to the median map is one seat (similar to the Partisan Advantage of 1.19 seats, as reported in Supplementary Table S9). Liu, Cho, and Wang (2016) generate over a million maps of North Carolina to evaluate its 2011 congressional maps. The map is an extreme outlier: the median, mode, or mean GOP seat difference between the enacted map and the ensemble is between 2 and 2.5 seats; more than double Chen and Cottrell's (2016) difference of one seat, but very close to the Partisan Advantage of 2.54 seats (Supplementary Table S9). Similarly, Cho (2019) generates three million simulated maps of Ohio to evaluate the state's 2011 congressional maps using 2008 and 2010 election results, and again she finds the enacted map is an outlier, granting three more seats to the GOP than the mode, median, or mean of the distribution of GOP seats in the ensemble.[75]

Returning to North Carolina's congressional maps, Chin, Herschlag, and Mattingly (2019) use yet another algorithm to generate an ensemble of 25,000 maps.[76] Using 2016 election results, they find that the 2011 congressional map of North Carolina is an outlier, under which the GOP obtains two additional seats relative to the median of the distribution of seats in the assembly. In related work, Herschlag et al. (2020) generate 66,500 maps of North Carolina and now, using 2012 and 2016 elections to the U.S. House, they find that both the 2011 congressional map and the 2016 remedial map result, on average, on a net gain of 2.5 seats per election to the GOP, relative to the median of the

[71]See Katz, King, and Rosenblatt (2020) for a discussion of these challenges. In fact, to sample for inclusion in the ensemble randomly from the universe of all admissible maps may not even be desirable, as most admissible maps are minimally compact, and perhaps we prefer to over-sample maps that are more compact (DeFord, Duchin, and Solomon 2020).

[72]They also use the same technique to evaluate the state legislative maps across 20 states.

[73]This result coincides almost exactly with the Partisan Advantage for the whole state of Florida using the 2012 presidential election result (3.06 additional seats to the GOP).

[74]In contrast, using all five U.S. House elections from 2012 to 2020, I find a Partisan Advantage greater than 5% for the Democratic Party only in the maps of Maryland and Illinois, both drawn by Democratic legislatures, and I find a large aggregate Partisan Advantage for the GOP.

[75]This is again closer to the Partisan Advantage of 2.11 seats (Supplementary Table S9), than to Chen and Cottrell's (2016) value of less than one seat of gain for the Ohio GOP.

[76]Their algorithm is a Markov Chain Monte Carlo random process that, starting from a seed map, at each step flips a precinct at the boundary of a district to an adjacent district.

Table 4. Measures of GOP Net Bias in 2011 Congressional Maps

	Difference from ensemble's median	*Partisan Advantage*
NC	1.0 [a], 2.0 [b], 2.3 [c], 2.5 [d]	2.54
OH	0.9 [a], 3.0 [e]	2.11
MD	-0.3 [a], -1.0 [f]	-1.19
FL	1.0 [a,g], 3.0 [h]	3.06

Study: [a] Chen and Cottrell (2016); [b] Chin, Herschlag, and Mattingly (2019); [c] Liu, Cho, and Wang (2016); [d] Herschlag et al. (2020); [e] Cho (2019); [f] Cho and Liu (2016); [g] Chen and Rodden (2013); [h] Chen and Rodden (2015).

distribution of outcomes in the sample (the Partisan Advantage of these maps is 2.54 seats and 3.11 seats).

I collect all these findings of deviations from neutrality, comparing them to each other, and to the Partisan Advantage, in Table 4. The second column shows the difference with respect to the benchmark given by the median of the distribution in the referenced ensemble, and the third column shows the Partisan Advantage. Positive values indicate a net gain for the GOP, and negative values, for the Democratic Party.

The large difference from Chen and Cottrell's (2016) results to all other results illustrates how challenging it is to interpret the finding that a map is an outlier relative to a sample drawn by a given algorithm, when "an algorithm designed to generate maps of districts may take a biased sample of all possible legislative maps" (Magleby and Mosesson 2018).[77]

DeFord and Duchin (2019) use a different Markov Chain Monte Carlo algorithm, one they call "Recombination," to evaluate a proposed reform of the redistricting process in Virginia. In this case we do know the properties of the ensemble generated by the algorithm: maps are sampled with probability proportional to their compactness, as measured according to a specific graph-theoretic definition (DeFord, Duchin, and Solomon 2020). Chen and Stephanopoulos (2021) use a version of this Recombination algorithm to study the effects of the VRA on minority representation. The subsequent dispute between the authors and Spencer and Duchin (2021) over methodological subtleties underscores the complexity of these computational algorithms.[78]

The Partisan Advantage avoids these computational difficulties, taking a simpler approach. Instead of using as baseline a (hard to draw) random sample obtained from a (hard to define) set of admissible maps, it relies on a more transparent benchmark: the seat outcome that would emerge if we bypassed districting altogether, and we instead apportioned seats according to the state's jurisdictional map.

6. CONCLUSION

The measure of Partisan Advantage in redistricting quantifies deviations from a seat benchmark based on representation by jurisdictions such as counties and townships. It measures the partisan advantage that is due specifically to the redistricting process, and not due to geographic sorting of the voting population. I find that the aggregate Partisan Advantage for the Republican Party in the 2012–2020 U.S. House elections averages 17 seats.

State by state, I find that the congressional district maps in North Carolina, Utah, and Ohio exhibit the greatest Partisan Advantage that is robust across several sensitivity tests. An in-depth discussion of the properties and limitations of the Partisan Advantage, and detailed state-by-state results, are available in the Supplementary Appendix.

The immediate purpose of the Partisan Advantage is to serve as a tool to identify which redistricting maps favor a party, relative to a simple neutral baseline, so that legislators and commissioners can draw neutral maps, and courts can more easily identify maps that are not neutral, if these are drawn and challenged in Court (as I discuss in Section 2). The ultimate goal is to contribute to running elections with a fairer representation of the citizenry's preferences.

SUPPLEMENTARY MATERIAL

Supplementary Appendix
Supplementary Table S1
Supplementary Table S2
Supplementary Table S3
Supplementary Table S4
Supplementary Table S5
Supplementary Table S6
Supplementary Table S7
Supplementary Table S8
Supplementary Table S9
Supplementary Table S10
Supplementary Table S11
Supplementary Table S12

[77]The comparison is not apples-to-apples because the three approaches use different election data, which can also contribute to the different results. The conceptual argument stands though.
[78]See, for instance, footnote 149 in Chen and Stephanopoulos (2021).

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Received for publication September 12, 2020; received in revised form July 26, 2021; accepted August 9, 2021; published online October 8, 2021.