Supreme Court of Ohio Clerk of Court - Filed April 25, 2022 - Case No. 2022-0298

IN THE SUPREME COURT OF OHIO

Meryl Neiman, *et al.*, **League of Women Voters of Ohio, *et al.*, Petitioners,** **v.** **Secretary of State Frank LaRose, *et al.*,** **Respondents.**	**Case No. 2022-0298** **Case No. 2022-0303** ***Consolidated*** Original Action Filed Pursuant to Ohio Constitution, Article XIX, Section 3(A)

PRESENTATION OF EVIDENCE BY RESPONDENTS HUFFMAN AND CUPP VOLUME III

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PRESENTATION OF EVIDENCE BY RESPONDENTS HUFFMAN AND CUPP

VOLUME III

Respondents, Speaker of the Ohio House of Representatives Robert Cupp, and Senate President Matthew Huffman, submit the following evidence in this matter[1]:

Exhibit	Item Description	Page No.
1	Transcript of Ohio Redistircting Commission Meeting dated February 23, 2022	HC001-HC024
2	Transcirpt of Ohio Redistricting Commission Meeting dated February 24, 2022	HC025-HC091
3	Transcript of Ohio Redistricting Commission Hearing dated March 1, 2022	HC092-HC143
4	Transcript of Ohio Redistricting Commission Meeting dated March 2, 2022	HC144-HC190
5	Attorney General Opinion to Speaker Cupp	HC191-HC205
6	Compactness Report for enacted March 2, 2022 Congressional Plan	HC206-HC209
7	Compactness Report for proposed Democratic Plan	HC210-HC213
8	Compactness Report for proposed Imai Plan	HC214-HC217
Volume II		
9	Speaker Cupp's Responses to LWVO Second Interrogatories	HC218-HC233
10	Speaker Cupp's Responses to LWVO Second Set of Requests for Production	HC234-HC248
11	Speaker Cupp's Responses to Neiman First Interrogatories	HC249-HC262
12	Speaker Cupp's Responses to Neiman First Set of Requests for Production	HC263-HC275
13	Senate President Huffman's Responses to LWVO Second Interrogatories	HC276-HC291
14	Senate President Huffman's Responses to LWVO Second Requests for Production	HC292-HC305
15	Senate President Huffman's to Neiman First Interrogatories	HC306-HC320
16	Senate President Huffman's to Neiman First Set of Requests for Production	HC321-HC332
17	Mr. Raymond DiRossi's Responses to Document Subpoena	HC333-HC343

[1] Respondents Huffman and Cupp also reserve the right to rely on any evidence presented in this matter by stipulation or presented by any party.

18	Mr. Blake Springhetti's Responses to Document Subpoena	HC344-HC354
19	SPRINGHETTI000003	HC355-HC356
20	SPRINGHETTI000053	HC357-HC358
21	SPRINGHETTI000058	HC359-HC360
Volume III		
22	Testimony of Dr. Kosuke Imai, Ph.D. *Graham et al v. Adams et al* Civil Action No. 22-00047, Commonwealth of Kentucky, Franklin Circuit Court, April 5, 2022.	HC361-HC556
23	Expert Report of Sean Trende	HC557-HC569

Respectfully submitted this the 25th day of April, 2022.

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CERTIFICATE OF SERVICE

The foregoing document was served on all counsel in this matter listed below on the 25th of April, 2022 via email

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Exhibit 22

COMMONWEALTH OF KENTUCKY
FRANKLIN CIRCUIT COURT
DIVISION II
CIVIL ACTION No. 22-00047

DERRICK GRAHAM, JILL ROBINSON, MARY LYNN COLLINS, KATIMA SMITH-WILLIS, JOSEPH SMITH, and THE KENTUCKY DEMOCRATIC PARTY,

Plaintiffs,

vs.

MICHAEL ADAMS, in his official capacity as Secretary of State of the Commonwealth of Kentucky and THE KENTUCKY STATE BOARD OF ELECTIONS,

Defendants,

And

COMMONWEALTH OF KENTUCKY,

Intervening Defendant.

PARTIAL TRANSCRIPT OF PROCEEDINGS
Testimony of Kosuke Imai, Ph.D.

BEFORE THE HONORABLE THOMAS D. WINGATE

MONDAY, APRIL 5, 2022

Transcribed by: Denise Myers Byrd, CSR 8340

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THE COURT: All right. Now, I thought that we would probably -- you don't need to do openings or anything. I thought you'd just go right into your witnesses and we go from there.

Is that all right, Michael?

MICHAEL: We'll pass, Your Honor.

THE COURT: Okay. I'll probably call you all by your first names; I know you. Okay.

All right. You can call your first witness.

UNIDENTIFIED COUNSEL: Your Honor.

THE COURT: Yes.

UNIDENTIFIED COUNSEL: Just two quick housekeeping measures.

THE COURT: Sure.

UNIDENTIFIED COUNSEL: So the first one is, yesterday we filed a motion -- a response to the motion to dismiss. We don't intend to argue that today, but wanted you to know that it is in the record.

THE COURT: Okay.

UNIDENTIFIED COUNSEL: At the end of the proceeding this week, we would expect to ask for judgment on our cross claim and counterclaim.

The second one is we have prepared a written statement of the joint stipulation that was reached at the last oral hearing.

THE COURT: Okay.

UNIDENTIFIED COUNSEL: So we would, you know, tender that to the Court. And we have included in a binder, for everyone's use, certain printed materials that we think would be helpful that come from either the LRC website or the Secretary of State's website both of which have been stipulated as admissible by all parties.

I think that's right, Casey.

ATTORNEY HINKLE: No objection.

THE COURT: What's your name again?

ATTORNEY HINKLE: Casey Hinkle, Your Honor.

THE COURT: I'm sorry.

ATTORNEY HINKLE: Casey Hinkle.

THE COURT: Casey. Okay.

So you have these stipulations written out.

ATTORNEY HINKLE: I believe --

UNIDENTIFIED COUNSEL: Yes, Your Honor. Alex is going to give it to the Court. We have

not yet filed it. We are tendering it here in open court. He's also giving you a notebook that we've already provided to the plaintiffs' counsel that includes relevant materials from the websites.

THE COURT: Okay. Can I just do the joint stipulation as Exhibit 1? Would that be all right for y'all?

UNIDENTIFIED COUNSEL: That would be great.

THE COURT: Okay. Unless you've got your --

ATTORNEY HINKLE: I did pre-mark a couple things, but that's okay.

THE COURT: You did. Okay. Well, if you pre-marked stuff, let's go with your pre-marked stuff and then we'll do this at break between your case.

ATTORNEY HINKLE: Okay.

THE COURT: All right. You may begin.

ATTORNEY HINKLE: Your Honor, similarly, I wanted to bring your attention. There are a couple of binders that we put over there as well.

THE COURT: Is that your binder?

ATTORNEY HINKLE: It's our binders, yes. And there's an empty binder for the witness's use, to keep things organized as he may receive a lot of paper.

THE COURT: Well, let's just go back and forth and take it to him. How's that?

ATTORNEY HINKLE: That's fine.

THE COURT: Or you can put your witness binders on up the witness stand if you wanted to go ahead and do that.

ATTORNEY HINKLE: Okay. You'd like the witness to be seated here?

THE COURT: That's where they're going to be.

ATTORNEY HINKLE: Okay. Great.

THE COURT: So however y'all want to do it.

ATTORNEY HINKLE: All right. Well, the --

THE COURT: I've designed this courtroom, so if you all hate it, it was designed by me.

UNIDENTIFIED COUNSEL: We love it, Your Honor.

THE COURT: Well, it's sort of like if

you're in a jury trial where you say voir dire, voir dire, you know, and I said "How do you say that" to one lawyer one time, and he said "However you say it is correct, Judge."

But anyway, it's designed just like the historical courtroom. That's -- you know, that's why.

All right. You ready to go?

ATTORNEY HINKLE: Yes, Your Honor.

THE COURT: All right.

ATTORNEY HINKLE: Plaintiffs call Dr. Kosuke Imai.

THE COURT: Okay. Please raise your right hand. Do you swear or affirm the testimony you're about to give this Court today is the truth and nothing but the truth?

THE WITNESS: Yes.

THE COURT: Okay. Now, how do you say your name again.

THE WITNESS: Kosuke Imai.

THE COURT: Okay. Thank you.

ATTORNEY HINKLE: Your Honor, would you prefer the witness sit so that you can see his face?

THE COURT: Nope.

ATTORNEY HINKLE: Or he face the audience.

THE COURT: I'm watching him on my monitor.

ATTORNEY HINKLE: I see. Thank you.

DR. KOSUKE IMAI,

called as a witness for the Plaintiffs, testified as follows:

DIRECT EXAMINATION

BY ATTORNEY HINKLE:

Q. Good morning, Dr. Imai.

A. Good morning.

Q. Would you please state your name for the record.

A. Kosuke Imai.

Q. And where do you live, Dr. Imai?

A. I live in Newton, Massachusetts.

Q. And what is your current occupation?

A. I'm a professor in the Department of Government and also in the Department of Statistics at Harvard University.

UNIDENTIFIED COUNSEL: Your Honor, may I interrupt. I'm having a hard time hearing him. Would you object if I moved over into the jury box.

THE COURT: No. Any of y'all need to

move over to the jury box, that's fine.

ATTORNEY HINKLE: And will you let us know if the courtroom microphone is not picking him up clearly.

THE COURT: Yeah. You just have to sort of speak in the microphone. The microphone is on even though the lights are not there.

ATTORNEY HINKLE: Okay.

THE COURT: Who's 18? Which one is 18? LEX 18? She's telling me that you're blocking the camera. There we go. Is that okay?

UNIDENTIFIED SPEAKER: Can Dr. Imai speak really fast.

ATTORNEY HINKLE: Just to test the microphone.

THE COURT: Can you say something so we can see if the cameras are okay.

THE WITNESS: I'm Kosuke Imai.

THE COURT: That's perfect.

UNIDENTIFIED SPEAKER: Yes.

THE COURT: All right. Thank you. That's all you need to do.

BY ATTORNEY HINKLE:

Q. So, Dr. Imai, you flew in from Newton, Massachusetts, you said, and you explained that

you're a professor at Harvard; is that right?

A. That's right.

Q. I'm going to ask you a little bit more about your academic background --

A. Okay.

Q. -- and qualifications. Because you've been retained as an expert witness for the plaintiffs in this matter, right?

A. That's correct.

ATTORNEY HINKLE: So, Your Honor, if I could approach the witness.

THE COURT: Sure.

ATTORNEY HINKLE: I have Dr. Imai's c.v. which he may want to reference during his testimony.

THE COURT: You got one for me.

ATTORNEY HINKLE: This is a copy for you.

THE COURT: Thank you.

ATTORNEY HINKLE: You can use this binder, if you'd like, to keep things organized that way.

And we've marked Dr. Imai's c.v. as Exhibit 1 for identification at this point.

///

(WHEREUPON, Plaintiff's Exhibit 1 was marked for identification.)

BY ATTORNEY HINKLE:

Q. Dr. Imai, is this an accurate and up-to-date c.v. that you prepared?

A. Yes, I believe so.

Q. And does this reflect your academic training and certain other of your experience?

A. Yes, I do -- it does.

Q. Okay.

ATTORNEY HINKLE: We would move to introduce this as Exhibit 1.

THE COURT: Do you have any objection to the c.v.?

UNIDENTIFIED COUNSEL: No objection, Your Honor.

THE COURT: Okay. So ordered.

(WHEREUPON, Plaintiff's Exhibit 1 was admitted into evidence.)

BY ATTORNEY HINKLE:

Q. And, Dr. Imai, can you start by telling us where you did your undergraduate studies.

A. I did my undergraduate studies at the University of Tokyo.

Q. And what did you study there? What subjects?

A. Major, you know, liberal arts which combines a variety of subjects, from mathematics to social sciences of your choice basically.
Q. Okay. And did you continue your studies after that degree?
A. That's correct.
Q. Where did you study next?
A. I did the graduate degree at Harvard.
Q. And what was the subject matter of that degree?
A. So I did study both statistics and political science, and statistics -- I received master's degree in statistics and Ph.D. subsequently in political science.
Q. And did you have a concentration within those fields of study?
A. Yes. I mean, you know, statistics in general and the application of statistics to social science, problems, questions, sometimes they call political methodology, so statistical methods for political science.
Q. And what are your interests in those topics? Why did you choose that as your concentration?
A. Oh, that's a good question. I was always interested in mathematics, computer science, you know, from a young age, but I was also

interested in social problems, problem -- politics, economics, sociology, so just as a way to combine my interest in mathematics and data with substantive interest in societal problems.

Q. Okay. Your c.v. lists various honors and awards, I think, on pages 2 and 3. One is a recognition by Clarivate Analytics as a highly cited researcher. Can you explain to us what that means.

A. Yes. This organization is a premiere organization that keeps track citation counts of academic journals, and I was named for -- one of the few people who had, I think, produced multiple papers of high citation impact, so I received that honor for the last four years, since that honor existed.

Q. And you received a Ph.D. degree from Harvard; is that right?

A. That's correct.

Q. And that was in 2002?

A. Uh-huh. In '03. Yes.

Q. Okay. What did you do after you received that degree?

A. Yes. So I started teaching at Princeton University first as an instructor and then

assistant professor, associate professor, and then I eventually promoted to full professor.

Q. And what classes did you teach?

A. Yes. So I teach, you know, statistics from undergraduate level to graduate level, mostly targeting students who are majoring in political science, public policy, you know, some engineering students who are interested in social problems as well, so those are the subjects that I teach.

Q. Okay. I saw a reference on your c.v. to Princeton's program and statistics and machine learning. Can you describe for us what that is.

A. Yeah. Sure. As you know, like, the last ten years many universities have invested data science programs, so Princeton was also, you know, no exception, they wanted to build the program that combines variety of disciplines from social sciences to engineering and even humanities, so there was interdisciplinary program they were building, and I was program director trying to coordinate, you know, variety of educational and other efforts in the area of data science.

Q. Thank you.

And the position that you had with Princeton, was that a tenure track position?

A. Yes. So I started as a tenure track assistant -- you know, instructor and assistant professor and then promoted to -- associate professor is tenure and then full professor is tenure.

Q. Do you receive tenure at Princeton?

A. Yes.

Q. And you at some point became a professor at Harvard University.

A. Right. That's right. So I was recruited by Harvard in 2018.

Q. And so you moved there in 2018. What is your position at Harvard?

A. I hold the position -- a tenured professor -- full professor position in both government department, which is the political science department at Harvard, and statistics department. And this is actually the first such joint appointment in the history of Harvard.

Q. And is this a tenured position?

A. Yes.

Q. I saw a reference on your c.v. to Harvard's Institute for Quantitative Social Science. Can

you explain to us what that is.

A. Yes. So the Institute of Quantitative Social Science is interdisciplinary institute at Harvard which basically brings all the people who studies statistics, machine learning, computer science, and focusing on social science problems, and so I'm part of that institute.

Q. Okay. What is your role with the institute?

A. You know, I'm just a member of the institute. I actively participate and organize workshops, you know, advise graduate students, and I play a variety of roles there.

Q. And I assume you do research as an academic.

A. Yes, I do.

Q. What are your main areas of research?

A. Yeah. So my main areas of research, there are two of them. One is what we call causal inference. This is studying cause and effect. And in my case, I focus on cause and effects of public policy, different programs, government programs, [unintelligible] organizational activities.

The second area of interest, which is perhaps more relevant for this case, is computational social science. So this is the

area where you develop computational algorithms to address and study social problems such as redistricting.

Q. And have you published any books in your academic career?

A. Yes. I have published book with the Princeton University Press 2017, I think, and this is a textbook for quantitative social science. So this is introductory textbook for undergraduate students and beginning graduate students who are interested in studying statistics and machine learning for social science problems that's being widely used across major universities in their teaching criterion.

Q. And in addition to the textbook, you've also written various articles, right?

A. Yes, I have.

Q. And are those listed in your c.v.?

A. Yes. They are all listed in my c.v.

Q. And are these articles, have they been published in journals that are peer-reviewed?

A. Yes. So I have I think more than 70 peer-reviewed journal publications.

Q. Okay. And those I think are listed on pages 4 through 9 of your c.v.; is that right?

A. Yes. Yeah, I think so. Yeah, that's right.
Q. Does Harvard have a society for -- excuse me.
Are you familiar with an organization called the Society for Political Methodology?
A. Yes. It is -- the Society for Political Methodologies are international organization. It's premiere academic society that -- basically, for the scholars to study using statistics and machine learning to study political science, basically.
Q. And are you a member of that society?
A. Yes, I'm a member of the society, and I also served as the president from 2017 to 2019 of that society.
Q. And how did you become president of that society? Was there an election or something?
A. Yes. I was elected as the president.
Q. And who are the members of that society?
A. So the members of the society -- there are more than 1,000 academic scholars, basically. Many of them are based in the United States, but there are many others who are based in Europe and Asia, so it's an international organization.
Q. Dr. Imai, you're here today to testify about redistricting. I would like to start just by

generally asking what type of analysis you used to analyze the redistricting questions that are presented by this case.

A. So I specialize simulation algorithms. I have developed several such algorithms in the past, so I use those algorithms to evaluate redistricting plans. And that's the type of analysis I have experience in and I conducted for this case.

Q. Okay. And I'd like to ask you to explain, in a general sense, if you can, how the simulation analysis works. Do you start with certain inputs?

A. Yeah. So usually the goal of simulation analysis is to evaluate certain characteristics of the proposed or enacted plan. And to do that, what the simulation algorithm does, is that you specify a set of inputs, so the inputs include the data, so data is often come from the census, the population data, and then also a set of criteria. So you might be interested in, you know, a set of legal criteria. For example, you want the districts to be contiguous or districts to have equal population, you know, or maybe that you want districts to be compact. So you

will input the data as well as a set of these criteria, so that's the choice of the analyst, and then what the algorithm does is it will generate a representative set of the plans, the redistricting plans, alternative redistricting plans that are consistent with those criteria you specified based on the data you input. So that's basically what the simulation algorithm does.

Q. Okay. And can you talk a little bit more about the criteria or constraints that you feed into the algorithm. Are there certain hard constraints? You know, can you assign weight to them? If you could explain that to the Court, please.

A. Yeah, so that's a very good question.

So there are two types of constraints that you can basically put in. Okay. So the first type is what I might call hard constraints, so these are the constraints that ensures that every single simulated plan was satisfied. So, for example, in my algorithm, I would put like contiguity as a hard constraint; that is, every plan the algorithm simulates has a contiguous district. There's no plan that

will have discontiguous, you know, simulated plan.

The other set of constraint you can think of it as soft constraint, so these are the constraints that often satisfy by the various degrees. So you can think of like -- a good example of this is compactness. So compactness is a measure of continuum. It's not a dichotomy of whether a district is [unintelligible] mathematically. A district is compact or not compact. There's more compact or less compact.

So in these soft constraints, you basically provide the different degree of weight, so how much compactness you want to, you know, impose, you have to do some other constraints.

Q. Okay. And can you describe a little more for us what the output of the simulation algorithm is.

A. Yeah. Simulation algorithm is -- literally the output is many maps, and what's really important about the characteristics of these maps is that they are representative of the alternative plans that are consistent with the set of criteria you specify. So think of this as, you know, like a similar [unintelligible]. There are many, many

districts you can draw under a set of constraints. It's impossible -- actually, astronomical number. It's impossible to enumerate every single possible map. So instead of trying to do that, because that's computationally impossible, what we try to do is we try to obtain a representative sample of that set, and that way we can characterize what that set will look like by just using this sample that we obtained.

And this is very similar to surveys. Like instead of interviewing 200 million American voters, you sample, say, a thousand people or 2,000 people. And the reason why we do that is because that sample is representative of the population of American voters so we can understand their opinion, for example, by just analyzing the survey -- or survey sample.

Q. And what are the applications for the simulation algorithm? What can it be used to do?

A. Yeah. So the main application of the simulation algorithm -- redistricting simulation algorithm is to evaluate, you know, the characteristic, whether it's partisanship or some other partisan bias or some other characteristic, racial

dimension of the enacted plan. What's -- yeah, so that's sort of the -- evaluation is, you know, the main goal of the simulation algorithm.

Q. Can the simulation algorithm be used to create a map that might be enacted into law?

A. So no. So my opinion is the simulation algorithm is used to evaluate, you know, how biased a particular map is, but it's not designed to generate a map that can then -- somebody can -- some state can take it and then enact it as a map. That's a role for the policymakers.

Q. Okay. And I think you mentioned that the map can be used to evaluate or -- excuse me.

The algorithm can be used to evaluate an enacted plan. By what measures? In other words, what could the algorithm be used to test for?

A. Right. So you can -- basically, once you obtain the simulated plan that's representative of the plans that are consistent with the constraints you place, then you can compare that with enacted plan and then see whether the enacted plan, you know, for example, favors a particular party in comparison to the simulated plan,

right. So if the enacted plan is favoring a particular party way more than the simulated plan, you think that there is something beyond the set of factors you specified that led to that bias.

Q. How long have simulation algorithms been used to evaluate redistricting plans?

A. Yeah, that's a very good question. I think in the court -- in the court -- in academic literature -- I've been studying simulation algorithms for ten years. I was one of the first academic researchers who really started developing the Monte Carlo method which has this representativeness characteristics, mathematical characteristics, but I think in the court, my understanding is that over the last five, six years the simulation algorithms have been used in a variety of courts across the country.

Q. If you know, how were redistricting plans evaluated prior to the innovation of the simulation algorithm approach?

A. Yeah. I think the biggest advantage of the simulation algorithm over traditional sort of way of evaluating redistricting plans -- by traditional way, I mean that usually what

researchers have done in the past is to compute some bias metrics for the enacted plan, for example, and then you say, okay, compare to this biased metric -- let's compare this, you know, metric with biased metrics of some other plans. So those plans may come from Massachusetts or New York or Ohio or somewhere else, and compared to those plans, this plan that we're trying to evaluate is biased.

But as you can, you know, all probably can tell, such a comparison is problematic because -- well, Kentucky is very different from Massachusetts, I think everybody agrees with that, and so you're now comparing apples and apples, right. You're really comparing -- you don't know why -- whether a particular plan is biased if you're just comparing that with other states -- a plan from other states. You can do the same thing within the same state. Like you can compare it with the previous plan, but that could also be problematic because the rules can change or the population could change, so things could change and so you're not really comparing the same thing.

So what the major advantage of the

simulation algorithm is basically you use the same data, right, in my case 2020 census data, and same set of rules, right, same set of rules that Kentucky requires, and then be able to generate alternative plans that are consistent with those data and rules instead of comparing with some other states, some other different rules or the previous, you know, plan.

So that's the major advantage, and I think that's why in at least academic circles this became -- this has become the dominant method to evaluate the redistricting plans.

Q. Are there different types of algorithms that are used?

A. Yes, there are different types of algorithms that are used to do this. They all belong to something called Monte Carlo methods. So it's a big family of methods. It's called Monte Carlo methods. Monte Carlo methods basically guarantees that -- there's a mathematical guarantee for the representativeness of the plans that you obtain.

As I said, it's impossible to enumerate all plans, so you obtain a random sample, representative plan. Within the Monte Carlo

family, there are two types of algorithms. One is called Markov chain be Monte Carlo. So Markov chain Monte Carlo is -- you start with a particular map and then we call this merge and split. So you randomly pick two districts that are adjacent to each other and then split and then you randomly pick two districts adjacent to each other, merge them and split. That's why we call it merge and split, and then we repeat this many, many times to obtain different maps, but it's done in a way that the resulting -- resulting simulated plans are actually representative of the population of the plans you're interested in.

The second one is a sequential Monte Carlo, or some people call SMC. SMC starts from the blank state, okay, and then creates one district at a time, so you create one district -- you randomly create one district and then you create another district and you create another district until you create all the necessary districts. So instead of starting like an MCMC, you start from the particular map and then start changing it. SMC, you start from the blank state and then you start creating the

districts.

But both are designed to sample from -- you know, obtain representative sample from the population of plans that you're interested in, so they serve the same purpose, it's just different techniques to achieve that goal.

Q. With respect to the MCMC method, the Markov chain Monte Carlo method that starts from an existing map, if that's the starting point for the algorithm, won't that starting point map always look like an outlier in any analysis that you do?

A. No. No. So that's -- well, that's incorrect in couple ways.

So first, Markov chain Monte Carlo has a mathematical guarantee that, you know, the resulting plans are representative. And typically what we do is we worry about -- you know, starting with, say, an enacted plan, the next plan will be different from the enacted plan, but it might be actually really similar, because we're just sort of merging the districts and then splitting in different ways.

So what we do is something called burn

in. We just discard the initial set of plans, certain number of plans so that there is less impact of the initial plan on the resulting -- you know, resulting simulated plans. So this type of practice is already established. It's not -- Markov chain Monte Carlo has been around for many decades, and it's an established practice to make sure that initial plan does not have impact on the resulting plans that you obtain.

Q. And so discarding those initial plans that are created is called burn in?

A. Yeah, it's called burn in, and we do that -- I do that in my report [unintelligible] in my report as well.

Q. And are the two different types of algorithms that you've described, sequential Monte Carlo and then the Markov chain Monte Carlo, are they designed to do different things?

A. In theory, they're designed to do the same thing. Now, in practice -- you know, redistricting can -- you know, redistricting case can be quite different from state to state. Like some states are larger. State house district we have 100 districts instead of six

districts in a congressional case. So, you know, some states there are population centers and some states impose complex rules, so depending on the situation, you want to be able to use different algorithm. And, you know, I can get into more detail of that, but, you know, based on my experience and expertise, I deciding which case -- which algorithm is more appropriate given the particular setting that I'm analyzing.

Q. And did you use both types of algorithms for the analysis you did in this case?

A. That's right. So for the house districts, I used the merge-split algorithm, which is MCMC algorithm, and then for the congressional district I used the sequential Monte Carlo.

Q. And can you just tell us why you chose to use the MCMC approach for the house map in this situation.

A. Yes. So the house map has 100 districts, as I mentioned, and then it also, as part of analysis, there is the -- sort of some more complicated restrictions on how the county splits should be done. And so these types of, you know, large number of districts with some

more complex constraints, the merge-split is a better way of sampling the simulated plans.

For the congressional districts, there's only six districts, relatively small number of districts, and there are sort of fewer rules that I needed to impose, and so for those cases the sequential Monte Carlo is very effective. Because unlike merge-split, which sort of sequentially alters the districting plan, you know, SMC spits out a simulated plan one at a time, so they're independent, like each one is separately generated, so it's more efficient way of obtaining the sample.

Q. Have you had any role in developing the methods you've just described for us, the two types of algorithms as used to evaluate redistricting plans?

A. Yes. So I have, you know, published, you know, a few articles that develop both type of methods, MCMC as well as SMC.

Q. And do you use a particular type of software to effectuate -- or run the algorithm?

A. Yes. So I use the software package called redist. It's based on the R programming language, which is one of the popular

statistical programming languages, and this is a software that my collaborators and I have developed over a few years.

Q. And is the redist software package something that anyone can use?

A. Yes. So one of the things I wanted to do, and this is part of my academic principle, is to make the methods available to everyone for free, so the reason is that it allows other researchers to duplicate and reproduce my results, which is important for scientific transparency and, you know, improvement, but it also allows other policymakers to use this.

And it's all free and open source. So open source means that the code is available, so anyone can look at the code that underlies the algorithm. And, you know, if there's a mistake, they can point that out, or if there's improvement that can be made, they can do that as well. And so that's -- unlike commercial software where the source code is not available, these are open source, free for download by anyone.

Q. And do you do anything to track how much the redist software package has been used by others?

A. Right. So I don't track download counts, but somebody else does. So there is a web page that keeps track download counts, you know, from several repository where this software is housed. And according to their counts, there are more than 30,000 times that software has been downloaded.

Q. Are you aware of any other academics or professionals that study redistricting using these same methodologies that you've innovated and described for the Court today?

A. Yes. So I've seen papers that -- by some other researchers who use this package as well as other expert witness in other cases who use this package.

Q. And there's something in your c.v. called the Algorithm-Assisted Redistricting Methodology Project, which is a mouthful.

A. Yeah.

Q. What is that organization or project? And can you describe for us what it does.

A. Yeah. It's a project that I had, you know, at Harvard which basically has a group of graduate students, undergraduate students who are interested in using simulation methods to, you

know, evaluate redistricting plans not only in the United States but also in other countries as well, so it's a research group that I lead.

Q. And, Dr. Imai, do you have any prior experience serving as an expert witness in litigation matters?

A. Yes. I've served on several cases.

Q. And are those matters listed at the end of your c.v. I believe on pages 25 and 26?

A. Yes, I believe so. Yes.

Q. And looks like there's seven cases listed there, including this one is number 7.

A. Yes, that's right.

Q. Did all of those cases involve redistricting proposals?

A. That's right.

Q. And what type of analysis, in general, did you do in those other cases? Is it similar to the simulation analysis you did here?

A. Yes. I only do simulation analysis. I'm the simulation guy.

Q. Okay. So that's the only subject matter expertise that --

A. Yeah.

Q. -- you've served in?

A. Yeah, that's my expertise. I feel comfortable.
Q. To your knowledge, have you ever had your expert report or your opinions excluded by a court in one of these cases?
A. I'm not aware of that.
Q. Are you aware of any challenge to your expert qualifications in any of those cases?
A. I'm not aware of that.

ATTORNEY HINKLE: Your Honor, we would offer Dr. Imai as an expert witness in computational science and in particular simulation analysis used to evaluate legislative redistricting proposals.

THE COURT: Okay.

ATTORNEY BECKER: No objection, Judge.

THE COURT: Okay. So ordered.

BY ATTORNEY HINKLE:
Q. So, Dr. Imai, you've been retained as an expert witness by the plaintiffs in this case, right?
A. That's correct.
Q. And are you being paid for your services?
A. Yes.
Q. Is the fee that you're charging for your services in this case a standard fee that you charge?

A. That's correct.
Q. Does the compensation that you receive in this case depend in any way on the opinions that you reach?
A. No.
Q. I also wanted to ask you, are you registered to vote in the United States?
A. No.
Q. And have you -- often in these disputes there's sort of a Democratic Party side and a Republican Party side in redistricting litigation.

Were you engaged by the Democratic side in all the cases that are listed in your c.v.?
A. Yeah, Democratic side, yes, but not necessarily Democratic Party for all the cases.
Q. Would you be willing to work for the Republican side in one of these disputes?
A. Sure.
Q. Have you ever been asked to do so?
A. Yeah. I've been just once by lawyer representing I'm not sure the Republican Party or the Republican side, but at that time, unfortunately, I was already engaged by the other side.
Q. In the same case?

A. Same case, yeah, had to decline.
Q. Have you ever turned down an expert engagement due to the political affiliation of the party requesting your services?
A. No.
Q. Have you ever turned down an expert engagement at all?
A. Yes, I have.
Q. And can you describe for us the circumstances in that situation.
A. Right. So I have, you know, declined one case I just mentioned. I was already engaged by the other side. I had to decline.

I also declined the engagement from the Democratic side in cases where I felt that the case they were trying to make didn't exist.

Q. In other words, where there -- where there wasn't good evidence of --
A. Right. So if I feel that critical evidence is not strong enough to support the case they are trying to make, I don't feel comfortable presenting my analysis.
Q. And that's happened before?
A. That happened before, yes.
Q. So when you were retained in this case, what

were you asked to do?

A. I was asked to analyze and evaluate the enacted plan, both house and congressional plan, using simulation algorithms.

Q. And did you produce a written report that reflects your opinions?

A. Yes, I did.

ATTORNEY HINKLE: Your Honor, may I approach.

THE COURT: Yes.

BY ATTORNEY HINKLE:

Q. Dr. Imai, if you could look at this document and let me know if that is an accurate copy of your expert report in this case.

A. Yes. Yes, that's the report I authored.

Q. And do you adopt the opinions that are reflected in that report --

A. Yes.

Q. -- as your opinions in this case?

ATTORNEY HINKLE: I would move to introduce Dr. Imai's expert report as Exhibit 2.

THE COURT: Any objection?

UNIDENTIFIED COUNSEL: No objection, Your Honor.

THE COURT: Okay. Thank you.

HC400

(WHEREUPON, Plaintiff's Exhibit 2 was marked for identification.)

BY ATTORNEY HINKLE:

Q. So, Dr. Imai, I'd like to ask you in a little more detail what you did to evaluate the plans for this case.

Did you have data regarding Kentucky's population that you used for the simulation analysis?

A. Yes.

Q. And where did you get that data?

A. I obtained that from census bureau.

Q. And did you get -- did you use any data regarding prior elections for purposes of your analysis?

A. Yes, I did. I used 2016 and 2019 statewide elections data.

Q. Where did you get the elections data that you used?

A. So this is called the VEST, Voting and Elections Science Team, that -- their data is hosted at the Harvard Dataverse, although the researchers who run this effort of collecting the precinct-level data are at the University of Florida and other universities.

Q. Did you say it's the Voting and Elections Science Team? Is that the source --

A. Yeah. It's called VEST, Voting and Elections Science Team. I think that's the full name.

Q. And to your knowledge, is that a widely used source of elections data?

A. Yes. So this is sort of the golden source for academic researchers, and it's available -- publicly available, and anyone can download that data as well, just like the census data that I used.

Q. Was the election data that you used available at the precinct level?

A. Yes.

Q. And with respect to the population data that you obtained from the census, how granular was that data?

A. So census data, the most granular level is available at the block level. However, because election data is -- you know, smallest unit for which election data available is precinct, so normally what academic researchers do, and what I followed, is to aggregate the census data, population data to the precinct level and then analyze the precinct-level data sets.

Q. So you mentioned that you used election results from 2016 and 2019 in Kentucky.

A. Uh-huh.

Q. Which races did you use?

A. Okay. So that's a question. So 2016, it was US presidential election and Senate election. And 2019, there was six statewide elections that I used: governor, lieutenant governor, attorney general, secretary of state, auditor, treasurer, and agricultural commissioner.

Q. And why did you choose those elections?

A. So these elections are all statewide elections for which the election data available at the precinct level to the best of my knowledge.

And the reason why the academic researchers typically use statewide elections is because when you do a simulation, you're trying to generate lots of districts that are obviously different boundaries from the, you know, district boundaries that were in the previous plan under which those elections were held. So if you look at, for example, like congressional election -- for example, like congressional election returns or the state house returns, those are based on the actual, you know,

district boundaries of the previous plans, and what we want to know is like what the partisanship would look like under different redistricting plans. So to do that we use the statewide elections where the district boundaries within the state doesn't exist so we can more accurately measure the partisanship of the districts that are under the simulated plans, so that's -- you know, that's the general practice.

Q. Does the algorithm that you use do anything to predict future election results or voting choices that voters may make?

A. No. I think of it as measuring the partisanship, partisan mean of each district under, you know, enacted plan as well as under simulated plan. I don't think of this as a forecasting model or exercise. In fact, you know, those models would require different type of inputs and statistical methods to do that.

So for me, these past elections are a way to measure the partisanship and partisan mean of different districting plans.

Q. So does the algorithm just assume that voters will vote the same way they have in these past

elections?

A. Well, it's more like algorithm will take the previous election results as a way to measure what the partisanship of the resulting district would look like. You know, actually, the algorithm itself doesn't use the partisanship, right. So algorithm uses the population that I used in my analysis only based on population data because you don't want to bias the results towards one party or another.

And so the algorithm itself doesn't use any partisanship information, but when you evaluate the enacted plan relative to the simulated plans, we're going to measure partisanship using the past election data, and that's -- you know, that's what's typically done in this type of analysis.

Q. So one of the redistricting plans you evaluated was for the Kentucky State House of Representatives.

What type of algorithm did you use to evaluate the house map?

A. So this house map, I used the Markov chain Monte Carlo, so that's the one that I used merge and split algorithm.

Q. And you explained to us why you made that choice.
A. Uh-huh.
Q. Is that choice something that other academics have also made? In other words, is there agreement in your field that the MCMC type of algorithm is best suited for something like the house plan?
A. That's a good question. I mean, I hate to sort of characterize as a general agreement just because, you know, you know US is a federalism and each state has such a unique set of rules and political geography, so I think it really depends on the set of circumstances you're in and trying to -- you know, also the goals -- the goals of analysis could be different depending on the case, so it could be partisan gerrymandering case or it could be racial gerrymandering case and different cases bring different analysis which may be based on different algorithms.
Q. Okay. So can you describe for the Court what criteria you fed into the algorithm for your state house analysis?
A. Sure. So what's nice about the simulation

algorithm is that it's very transparent in terms of input. So, you know, you list inputs and they go in and plans come out.

So the set of inputs I used is basically I told the simulation algorithm to generate a total of hundred contiguous districts for the house, and I also set the population deviation to be plus/minus 5 percent for the house, so at most 5 percent deviation from the equal population criteria. And I may show that the districts also at least as compact as the enacted plan on average based on the sort of set of measures that academics use to measure compactness. We try to minimize the number of counties that are being split by the districts. I also made sure that the simulated house plan had fewer county boundaries that split in comparison to the enacted plan on average. Also made sure that the simulated house plans have fewer districts with more than two counties, so the districts comprised with more than two counties in comparison to the enacted plan, so fewer of those. I also made sure that the simulated plans had fewer counties with more than two districts. So another way to think of

this is there's a county, and if there's more than two districts as part of that county, I tried to minimize -- reduce that number of such counties.

And importantly, I did not use partisanship or racial information in the simulation algorithm.

Q. Why didn't you feed the algorithm any partisanship criteria?

A. Right. So the purpose of this analysis is to evaluate the partisan bias of the enacted plan, so what you want to do then is to compare that enacted plan with the alternative plans that are consistent with all the rules, but, you know, you don't want to use the partisanship to generate biased plans, so I don't use partisanship when analyzing the partisan bias of the enacted plan.

Q. And why did you not feed the algorithm any information about the race of voters in Kentucky?

A. Right. So that also depends on the purpose of the analysis, but use of race can be, you know, biased in terms of like racial gerrymandering and also that for some analysis, like in -- you

know, depending on the case, you may consider like, you know, certain type of majority-minority districts, for example, to be created in certain parts of the state, but in those cases, you'd have to -- typically there has to be a VRA claim and there has to be some analysis that establishes, you know, where and -- you know, the majority-minority districts, where that should be located and what should be the percentage. So in this case I focused on analysis of partisan bias of the enacted plan.

Q. And you made a reference to the VRA. Is that the Voting Rights Act?

A. That's right, Voting Rights Act.

Q. And how many simulated plans did your algorithm generate for the house map?

A. So I basically generated a total of 10,000 simulated plans for me to analyze.

Q. And you mentioned the technique earlier called burn in.

A. Right.

Q. Is that something that you used here?

A. That's right. So, you know, in practice what you do is you generate more than what you want.

So in this case I wanted to generate 10,000, so you generate more than that. So in my case I generated 72,000. And burn in basically discards the initial simulated plans. I discarded, I think, 1,000 of them for each -- each chain, the parallel chains that goes in.

And then there's also a technique called thinning to make sure that the simulated plans are not too dependent, so I used that technique to -- this is a very sort of standard, general technique in the MCMC literature to obtain the final 10,000 simulated plans.

Q. Okay. Why not use as your set of simulations the original 72,000? Is there some reason that you need to thin down to 10,000?

A. Right. Yes. So this is, again, a standard practice in the MCMC literature, but the burn in is designed to reduce the impact of the initial plan, so initial thousand plan that's been discarded, and thinning is a way to reduce the dependency of the plan, and so that's what I did.

Q. And I'd like to get into what your analysis showed with respect to the Kentucky House plan.

A. Sure.
Q. And we're going to use some terminology today, and I want to make sure everyone understands what we mean.

You mentioned before that you applied a criteria to require the number of county splits to be minimized. We might call those split counties. Does that mean that all of your simulated plans have 23 split counties?
A. So in the -- for the house plan, the enacted plan actually has 23 counties that are being split. We can call this split counties. And the simulated plan, all of them, also have 23 exact, so in that sense, you know, should be plan equal to the enacted plan.
Q. And is that the minimum number of counties that need to be split?
A. I think so, yeah.
Q. And you did some further analysis of the 23 counties that were split, right?
A. That's correct.
Q. And your report references something called multi split counties. Can you just explain how you're using that term.
A. Right. So 23 counties that are being split is

the total number of counties that are split in some way, but you can imagine the county can be split in many different ways. Like county can split into, say, two districts or a county can split into three or four districts. So instead of just counting how many -- you know, counting how many counties are being split in some way, I looked at farther as to exactly how those counties are being split. So, yeah.

Q. And does Figure 1 in your expert report, which is on page 9, does that reflect your analysis of multi splits?

A. Right. So this is one analysis I did, which basically counting the number of counties -- like computing the number of counties that contain more than two districts. So instead of having one county split, you know, into two districts, it might split into three districts or four districts, so lots of splits within the county, so Figure 1 presents that.

Q. And can you describe for us what this -- what this figure shows.

A. Sure. So Figure 1 as -- first, I think you can look at red lines, so this is enacted plan. So enacted plan have 18 counties that has more than

two districts. So under enacted plan there are 18 counties that are not just split into two districts but three or four or more. Okay.

Under simulated plans, on average there are 15 counties, so on average three county [unintelligible] of such counties, and, you know, it ranges from 13 to 17.

Q. Okay. And is this the analysis that informed your opinion that the house plan unnecessarily splits a greater number of counties into more than two districts?

A. That's right. So this figure shows that it's possible to generate many, many maps, for this case I can even generate more, that have a fewer number of counties that has more than two districts than, you know, compared to the enacted plan.

Q. And you also counted the number of house districts that include all or part of more than two counties.

A. That's right. Yeah. So that's another way of thinking about how the counties are being split. You know, previous one is that look at the county and then count how many districts are in the county. Another way of thinking about it, I

can look at the district and then count how many counties are in the district. And so you can count the number of districts that has more than two -- two counties. Yeah.

Q. Is that analysis shown in Figure 2 of your report --

A. That's correct.

Q. -- which is on page 10?

A. That's correct.

Q. And can you show us what this analysis reflects.

A. Right. So again, this is similar to Figure 1. I forgot to mention that these gray bars are histograms, so it tells you [unintelligible] under simulated plans how often different number of districts with more than two counties happen.

And so under the enacted plan, there are 31 districts that has more than two counties whereas under simulated plans, you know, on average there are 24 such districts which is basically seven districts fewer than the enacted plan on average, and, you know, it ranges from 21 to 30.

Q. And is that difference statistically significant in your view?

A. Yes. In fact, now my 10,000 simulated plans has

as many districts or more with more than two districts, so in that sense it's outlier, the enacted plan is outlier, has way more districts with more than two counties than any of the 10,000 simulated plans.

Q. And I think you also looked at the total number of county splits in the enacted plan compared to your simulated plans.

A. That's correct.

Q. And I think that's Figure 9 of your report, right?

A. Yes.

Q. Which is on page 22. And can you just describe for us what this is quantifying or showing us.

A. Right. So, you know, this is just accounting for -- again, for each county you count the number of districts and then you add that number up across all counties in the state, and under enacted plan, there are 80 such splits -- additional splits more than necessary. And then this figure shows that on average the simulated plan has fewer additional county splits.

Q. Okay. Dr. Imai, are you aware that the defendants in this case have retained and disclosed some expert opinions?

A. Yes.
Q. And have you had an opportunity to review the defendant's disclosed experts which are Sean P. Trende and Dr. Stephen Voss?
A. Yes, I have had a chance to look at their reports.
Q. I'm going to ask you now about one of the critiques of your analysis in Dr. Voss's report.

He claimed that avoiding multi splits in your algorithm caused urban counties to be carved up such that urban centers are represented by more districts.

UNIDENTIFIED COUNSEL: Your Honor, we have a question about this procedure.

Whatever he is about to testify to has not been disclosed in any prior report, so this is outside the scope of what has been disclosed by Dr. Imai, and we think it's inappropriate.

ATTORNEY HINKLE: And, Your Honor, we would respond that it's within the scope of his initial opinions. He's just explaining why critiques that have been lobbed at his analysis are incorrect.

THE COURT: I agree with you. It's overruled. I think that your Dr. Voss can

critique Imai and Dr. Imai can critique Dr. Voss. I think that's fair enough. Okay.

ATTORNEY HINKLE: Okay.

THE COURT: Thank you.

BY ATTORNEY HINKLE:

Q. So Dr. Voss asserted that -- in one of his maps that he assessed is best for Democrats that only had 13 splits that there were certain cities, Bowling Green, Owensboro, and Hopkinsville, that are split up excessively I think is the assertion, and he actually said that he saw that across your set of simulated plans.

Did you do anything to evaluate that critique by Dr. Voss?

A. Yes.

Q. And can you describe for us what you did.

A. Yes. So one thing that's very important, and I think is incorrect in the Dr. Voss report, is that one should never look at a single or a particular map, simulated plans. In order to use the simulation for evaluation, you have to look at the distribution of plans, so not like one specific plan but all 10,000 of them to see, you know, in this case how often -- if you look across all 10,000, how often does a particular

city will being split among them.

So this is very similar to sort of something -- again, I can just show you an example of that where, you know, if you are interested in opinion of American voters and you sample 1,000 voters, you don't want to just look at one person who you happen to interview to infer what the Americans think of the whole. And so it's always important to look at, you know, all 10,000 plans and then see if there's a tendency that imposing these county split constraints will have some impact on a particular aspect of the plans you're interested in.

And when I look at Bowling Green, Owensboro --

Q. Hopkinsville.

A. -- Hopkinsville, basically the split constraints have no material impact on how often these cities are being split, so there's no empirical evidence that shows that these additional constraints have impact on these cities as he asserts.

Q. I just want to make clear what you did, make sure I understood what you said. So you removed

the multi split constraints that you fed into your algorithm and then looked at those three cities, Bowling Green, Owensboro, and Hopkinsville, and you observed, what, that there was no material change in the number of splits --

A. Yeah.

Q. -- in those urban centers?

A. And actually, that's exactly what Dr. Voss did. So Dr. Voss basically took my code and then he moved that particular constraint and then actually simulated plans, which I duplicated, I got the exact same simulated plans. However, he did not look at how often these plans split these cities. He just picked one map and then said look at this map, this map splits this city many times, this city many times, this city many times.

What I did is took the output of what he did and then actually look at how often these 10,000 maps split this city and this city and this city. And when I compared that with my initial simulation which had, you know, this constraint, there's no statistically significant difference. So what that suggests is that this

particular constraint that he moved has no material impact on those splits of those cities.

And this is, you know, another advantage of simulation algorithm is that actually you can add a constraint or remove it and then figure out whether that has any systematic impact. You know, the maps you're going to get is going to be different from the maps you get if you had -- you know, it's a random algorithm so it will generate different maps, but you need to look at, you know, whether these two sets of maps have different characteristics and tendencies.

Q. So the algorithm allows you to isolate --

A. Yeah.

Q. -- the impact of particular criteria?

A. Yeah, and Dr. Voss could have done that.

Q. Did you do any partisan bias analysis of the enacted house plan?

A. Yes, I did.

Q. And what did you do to evaluate that?

A. Yes. So I look at the -- you know, for each district I look at the parts of mean of that district based on those six elections that I mentioned, two elections from 2016 and, you

know, six elections -- statewide elections from 2019.

Q. And I'd like to ask you a little bit about the analysis that's reflected in Figure 3 in your report.

A. Sure.

Q. Which is on page 11 of the report. And this is one that we have enlarged in hopes that the Court and everyone else will be able to see it as Dr. Imai explains for us what is being shown.

Dr. Imai, if you'd like to come closer to point things out --

THE COURT: You can get up there and point to what -- it will pick you up with her microphone.

ATTORNEY HINKLE: And, Your Honor, if you could let us know if you're having any trouble seeing this. We may move it closer so that --

THE COURT: I can see it.

ATTORNEY HINKLE: Okay.

BY ATTORNEY HINKLE:

Q. Dr. Imai, can you walk us through what's being depicted here on Figure 3.

A. Okay. So this is a somewhat complicated figure,

but I'll try to explain. So what I did is for each plan, I ordered districts by Democratic vote share, so from the least Democratic district to the most Democratic district, you know, hundred districts of them.

And first I wanted to sort of ignore --

THE COURT: Let me ask you this: Are you doing registration? Is that how you get this?

THE WITNESS: Yeah, that's a very good question. So it's based on the vote share -- average vote share across the past elections, so --

THE COURT: So you're not just doing Democratic registration; you're doing voting patterns.

THE WITNESS: Voting patterns, yes.

THE COURT: Gotcha.

THE WITNESS: Exactly right, at the precinct level. Because it's measured at the precinct level, I can aggregate it to the district level to know whether a particular district has 40 percent Democratic vote share versus, you know, 60 percent Republican vote

share on average across the past elections for which I have data.

So first I want to ignore these funny boxes and focus on these red dots. So these red dots are basically enacted plan. In the house, there are a hundred districts, so if I do 100 dots, nobody can see anything, so I focus on the competitive districts that are closest to 50/50 line, which is the dotted line.

So all of this --

BY ATTORNEY HINKLE:

Q. Dr. Imai, I'm sorry to interrupt. I just want to clarify one thing.

There's reference to district numbers along the bottom of this graph. Are those the districts of the state house representative districts?

A. Yeah. So these numbers are not the particular district number. It's 73rd most Democratic -- you know, so the higher -- the higher the number is more Democratic it is and the lower the number is the least Democratic. So D 1 would be the least Democratic district; D 100 would be the most Democratic district. And I'm focusing on from 73 to the 84 that are closest to -- you

know, it's most competitive districts based on the past elections.

So what you see first is these red dots. On the Y axis, you see the Democratic vote share. So anything below the 50 percent is Republican-leaning, anything above the 50 percent is Democratic-leaning. And what you see for these -- these dots are enacted plans.

So, for example, you know, the 77th district, based on the order before Democratic vote share, in the enacted plan, the vote share is about -- Democratic vote share is about 47.5 percent points.

And so one thing I wanted to notice is the pattern. So below 50 percent, you see these red dots, you know, sort of flattened here and then there's a big gap, about 2.6 percentage point going from this particular 79th district, order district to the 80th district which now closest like Democratic -- you know, these districts Democratic-leaning because it's above 50 percent, okay.

So what this shows is that for the Democratic-leaning districts, these four districts remains -- these are actually

competitive, close to 50 percent, and yet the Republican-leaning districts tend to be far away from the 50 percent, so tends to be more safe. In fact, this district that's the closest to 50 percent is middle 48 percent, so this would be considered relatively safe Republican district.

UNIDENTIFIED COUNSEL: Casey, can he -- just "this district," was that D 79?

THE WITNESS: Yes, 79.

ATTORNEY HINKLE: That's right, yeah.

THE WITNESS: And this jump, going from D 79 to D 80, this big jump is in the academic literature considered -- call this type of pattern as signature of gerrymandering. Because basically the close Republican-leaning district in this case are made safer whereas the close Democratic-leaning districts are made to be competitive.

Now, what I did, then, was to compare this with the simulated plan, so not only just sort of seeing this pattern which is -- you know, it's often called the signature of gerrymandering in the literature, I want to know whether this is unusual, like I want to know

whether simulated plan also have this pattern.

Well, simulated plan, because there's 10,000 plans, I have box plot. So box plot basically shows that this box contains 50 percent of simulated plans, so 5,000 of them out of 10,000, and then these lines which are called whiskers are called typical range, typical range of simulated plan. And this is actually median.

And what you see is that simulated plan has no gap. It very smoothly shifts -- changing in terms of vote share from, you know, 73 to 84, and there's no, you know, jump anywhere. In fact, these two districts, or maybe even these three districts, 78, 79, 80, they tend to be Democratic-leaning on average whereas under enacted plan, these are safe Republican seats.

So what this comparison shows -- and then if you look at the Democratic-leaning districts that are very close to 50 percent, you see that these -- under enacted plan, this is much closer to the 50 percent line compared to the simulated plan.

So what this shows is under enacted plan, Democratic-leaning districts are being

made competitive -- more competitive than the simulation would show otherwise -- would show. And the Republican-leaning districts are being made safer relative to the simulated plan.

BY ATTORNEY HINKLE:

Q. Do you draw any conclusions from the data that's reflected on Figure 3?

A. Right. So this figure shows the evidence of partisan gerrymandering, favoring the Republican Party, by making Republican-leaning districts safer and making Democratic-leaning districts more competitive than -- compared to the simulated plans.

Q. And, Dr. Imai, can you comment on the strength of that conclusion or opinion?

A. Right. So in -- you know, if you think of statistical outliers, like, these are statistical outliers, beyond these, you know, typical range that you might -- you know, typical simulated plan range. And what you see is that not only just the one district but the pattern of several districts that are being made safer than the simulated plan would indicate.

And here again, it's all -- all these four districts are being made more competitive

in comparison to the simulated plan. So this pattern as a whole -- you know, as a statistician, I don't want to just put all my basket -- all my eggs in one basket, but if you look at the multiple districts, you see the pattern of partisan gerrymandering.

UNIDENTIFIED COUNSEL: I'm sorry. Can you -- if you look at which districts? Did you say marginal?

THE WITNESS: If you look at these districts that are, you know, closer to the 50 percent.

UNIDENTIFIED COUNSEL: I just didn't understand the word.

UNIDENTIFIED COUNSEL: Multiple.

THE WITNESS: Multiple.

UNIDENTIFIED COUNSEL: Multiple. Thank you.

BY ATTORNEY HINKLE:

Q. And, Dr. Imai, is the opinion that you just described, is that dependent on your observations about the enacted plan having more counties with multi splits than the simulated plans, or are those separate opinions?

A. Not -- yeah, they're separate opinions. You

know, they're obviously related, but they're separate opinions.

Q. And this analysis reflects your evaluation of Kentucky as a whole, right, all 100 districts?

A. Right, focusing on, you know, relatively competitive districts where, you know, redistricting could make a difference.

Q. Did you do any local analysis of partisan bias in the house map?

A. Yes, I did.

ATTORNEY HINKLE: Your Honor, if I may, I'm going to take this down.

THE COURT: Yes.

So let me ask one more question. Are these 12 specific districts that are the closest to being competitive?

THE WITNESS: That's correct. You know, under the enacted plan, there was specific districts that are close to, you know, competitive districts, as you said.

Under simulated plans, they're not necessarily the same districts because it's different plans, so the most competitive district may not be in the same location, it could be different parts of the state, but it

tells you how the competitive districts fair in terms of partisanship in comparison between the enacted plan and the simulated plan, you know, that's the analysis. And this is under the standard analysis the academic researchers do when evaluating the partisan bias of the enacted plan.

BY ATTORNEY HINKLE:

Q. You mentioned a term in your testimony about Figure 3 called the signature of gerrymandering.

Is that an accepted term in academic literature?

A. It's a term that has been published not by myself, other researchers in articles and academic journal.

Q. And it's commonly understood to refer to what you've --

UNIDENTIFIED COUNSEL: Objection, Your Honor. She's leading the witness.

THE COURT: He's an expert witness. It's all right. I'll let you lead too, Vic.

UNIDENTIFIED COUNSEL: Thank you. I'll take you up on it.

BY ATTORNEY HINKLE:

Q. All right. So I'd like to move on now to talk

about your local analysis that you did. I think you looked at Jefferson county and Fayette county, right?

A. That's right.

Q. And can you describe generally for us what you observed when you looked at those two localities.

A. Yeah. What you observe is a pattern of combining basically the Democratic voters in the urban area with the Republican voters in the rural area to create more Republican-leaning districts.

Q. And is your analysis of Jefferson county reflected on Figure 4 of your expert report that's on page 13?

A. (Witness nodding head up and down.)

Q. And I have that one in the large size as well.

A. So this map shows Jefferson county and the surrounding area. And on the left, the maps are covered by, again, the Democratic vote share based on the past elections under the enacted plan.

So under the enacted plan, you can see that Districts, you know, 42, 43, and 30 are very, very Democratic; 34, 41, 40, 44 reasonably

Democratic; and then in the rural area much more Republican -- Republican districts. And the gray line are county lines, county boundaries, and sorted black line are the district boundary lines under enacted plan.

So one thing you notice is -- let's look at, like, District 48, for example. So District 48 takes the sort of urban area of voters and then combines with part of Oldham, so it sort of crosses the county border and spills into this rural county that has very strong Republican-leaning tendency.

If you look at District 33, that's another example where you take the urban districts -- urban precincts and then combine it with the rural districts. In this case, this particular district cross into two other counties, so it's part of Jefferson, but it's also a part of Oldham and part of Shelby.

So these are the two districts who basically I see this pattern in other places where the urban -- urban precincts are combined with the strong Republican voter base of the rural -- rural counties and as a result the district becomes more Republican. So if you

look at the 48 and 33, the colors are a little bit pink which means that now these two districts, despite the fact that there are Democratic voters vote share becomes Republican-leaning.

Now, we don't want to just look at this. We want to compare this with the simulated plans. So the question is is this unusual or is this -- does this have to happen because of all this population constraints and contiguity and so on.

So on the right you see the same exact map except now the coloring is based on the average simulated plan so -- at the precinct level. So what you can see this is that for each precinct, wherever you look at it, you can ask yourself, okay, well, on average, how Democratic that district does precinct belong to under the simulated plan.

So what you see -- so let's look at 48 and 33. So if you look at 48, you see that slightly blue area here which means that these voters tend to belong to the district that's slightly Democratic-leaning under the simulated plan even though these voters in the enacted

plan is actually a part of District 48 which is Republican-leaning.

Now, going towards closer to more rural area, these voters tend to belong to more competitive districts. The white means Democrats and Republicans are very close, and yet under the enacted plan they're part of 48 which is Republican-leaning.

And this area, which is a part of Oldham, part of District 48, these voters actually tend to belong to more Republican district. That makes sense because these areas heavily Republican. So typically these voters would be a part of the district that is within Oldham. However, because these voters combined with the urban voters, 48 becomes essentially Republican-leaning district.

The same pattern appears in District 33. So if you look at the District 33 in the urban area, these voters, mostly Democratic, they tend to belong to the much more competitive district under simulated plan, but when they're combined with the Republican voters in the Oldham county and the Shelby county, then District 33 as a whole in the enacted plan

becomes -- becomes Republican-leaning.

So this pattern of, you know, combining basically the urban Democratic voters with often the rural county, by crossing the county voter and creating a district leads to, you know, Democratic voters belonging to more Republican-leaning districts in comparison to the simulated plan.

You see some of these pattens -- you know, even District 29, for example, these voters would belong to more competitive districts and yet under the simulated plan they would be part of the Republican-leaning district, so that's Jefferson.

Q. Do you have an opinion of what this pattern shows?

A. Right. So this pattern basically shows the strategy of combining the Democratic urban voters with the Republican rural voters to create the Republican-leaning district.

Q. And you did a similar analysis for Fayette county where Lexington is, right?

A. That's correct.

Q. And your analysis of Fayette county is shown in Figure 5 which is on page 15 of your report.

I'll try to hold this up a little straighter.

So, Dr. Imai, can you walk us through your analysis of Fayette county as shown in Figure 5.

A. Sure. So this is the same sort of set of figures that I just showed you for Jefferson. So on the left you have enacted plan, and on the right you have average simulation plan.

Under the enacted plan, the District 77, which is I think it's the most Democratic-leaning district in the state. And, you know, so in the sort of -- in the very urban areas there's a group of Democratic districts that's created, but I wanted to focus on District 88 and District 45.

So 88 takes the sort of surrounding [unintelligible] of this county and then spills over into Scott. Then this is the heavy Republican area. So by combining some of the Democratic voters who live in this area with the large number of Republican voters in the Scott county, this 88 becomes Republican-leaning.

Similarly, if you look at the 45, 45 takes some of the Democratic voters who live here and then combine it with a large number of

Republican voters who live in the Jefferson county, again, by crossing the county line, and this creates Republican-leaning district even though there are many Democratic voters live there.

Now, compare this with the simulated plan. So under the simulated plan, the voters who live in this area, which under the enacted plan part of it, District 88, they are more likely to belong to Democratic-leaning district. So, you know, in many cases, these voters who live around here is most likely to belong to the Democratic-leaning district. However, in the enacted plan, because it's combined with this large area of Scott county, 88 becomes Republican-leaning.

Similarly, the voters who live in 45 district on the enacted plan, these voters are more likely to belong to the competitive districts. That's why it's white under the simulated plan. And yet because of -- on the enacted plan, District 45 combines these voters with this large number of Republican voters in Jefferson county, the 45 becomes Republican-leaning district.

So this is, again, the same pattern as Jefferson where the urban Democratic voters are combined with rural Republican voters to create additional Republican-leaning districts, and this is achieved by packing Democratic voters in the center city. And you can see that these blue color is much darker than the blue colors under the simulated plan. So these voters in the center city generally belong to Democratic district because that's where they live. However, on the enacted plan, they are carved in a way that packs the Democratic voters but which then reduces the Democratic vote share or [unintelligible] of the surrounding county which helps create the additional Republican-leaning districts.

Q. Thank you.

Dr. Imai -- yeah, thanks -- did you -- I noted in the rebuttal reports there was a suggestion that maybe the multi split constraint that you fed into your algorithm impacted your observations with respect to partisan bias.

Did you do anything to investigate that critique?

A. Right. So I saw that critique that multi split

constraint that I imposed may have a partisan implication, and as I said in the previous criticism, it's very important to look at all the simulated plans, instead of just one or two simulated plans that were chosen in the rebuttal report. So what I did was just take the simulated plan, you know, Dr. Voss or Trende, I can't remember which, but they generated and then look at the -- basically recreate these figures, same set of figures, and I see no material difference, no statistical difference.

Q. Okay. One of the rebuttal experts, Mr. Trende, stated in his report that he calculated something called efficiency gap on all of the maps in your simulated set of 10,000 alternative house maps and asserted that the efficiency gap looks within normal range on the enacted plan under the analysis that he did.

Did you do anything to analyze Mr. Trende's opinions in that regard?

A. Yes, I did.

Q. And can you describe for us what you did.

A. So first, efficiency gap is a measure of partisan bias. It's a measure that's used quite often in academic literature as well as in many

court cases. It's not the only measure, but it's one way to measure partisan bias of a particular -- of a particular plan.

Should I explain what that is?

Q. Sure.

A. So the idea is that, you know, if -- if packing -- so it's trying to capture packing and cracking. So packing means that you try to pack, you know, opposing party voters/supporters into one district so that they have -- they have less -- you know, fewer chance of getting out of district -- the candidates elected in other district, so they look at the wasted votes, so how many votes are cast that's beyond 50 percent, so that's an unnecessary wasted votes.

The other part of this efficiency gap is that -- cracking which basically tries to crack the stronghold of the opposing party supporters so that you, you know, divide the supporters of a particular party into two districts. So in those cases you might lose election by, say, close margin but not quite enough, and so those votes get wasted, so they look at how the wasted votes defer between

Democrats and Republicans, so that's a measure that's one measure of partisan bias. It's not the only measure. There are other measures as well.

But what Mr. Trende did in his rebuttal report, and he calculated efficiency gap under enacted plan and then compared that with the simulated plans. You calculate the efficiency gap for each simulated plan and then look at the distribution of simulated plan -- efficiency gap on the simulated plan and then compare that with the efficiency gap of the enacted plan.

So that's a good thing in a sense that it's comparing the enacted plan with the simulated plan, like not just one plan, one simulated plan, but looking at the 10,000 simulated plans, so that's a good thing. However, what he did is to choose one particular election to compute this efficiency gap, and he chose 2016 presidential election.

Okay. When I look at the other elections -- so I can basically repeat the same exercise. But using the academic literature, you don't want to rely on a single election because a single election, as you know, has many

different factors going in. Some candidates may be extremely popular or less popular, there may be some other events that happened during the campaign that could influence it. So most of the academic literature, when investigating the partisan bias of a particular plan, you look at a wide range of races and then average them out. So when you average across different races, many of these factors may cancel and you get the general pattern of partisanship instead of relying on a particular election.

And so when I did that -- in fact, if I just take 2016, not just the US presidential election but also senate race, so those are two statewide races for which there is data available for 2016, then his results go away, but the analysis shows that enacted plan is an outlier favoring the Republican Party as measured using efficiency gap.

If I use 2019 election -- there's six of them -- I get the same results: The enacted plan is actually an outlier favoring the Republican Party based on efficiency gap measure.

If I take all of the elections, 2016,

2019 together and then compute the efficiency gap, I get the same exact results: The enacted plan is an outlier favoring the Republican Party over Democratic Party.

So what Mr. Trende did was to choose this particular election and was able to show, well, in that case, you know, the enacted plan was in a similar range, but as soon as you take more elections and combine them, which is the right way to do it because you don't want to rely, again, on a particular election, then his result goes away.

Q. I would like to move on to your evaluation of the enacted congressional map.

Did you analyze Kentucky's enacted congressional map --

A. Yes, I did.

Q. -- as part of your expert engagement?

And what type of algorithm did you use to evaluate this map?

A. So for this -- the congressional analysis, I used the SMC, the sequential Monte Carlo algorithm.

Q. And that's the approach that starts with a blank slate, right?

A. That's right. Yeah, the one that starts with the blank slate and then start building the district one at a time.

Q. And what criteria did you feed into your algorithm when you were evaluating the congressional map?

A. So I made sure that the algorithm creates a total of six contiguous districts, that's the number of congressional districts, and I used overall population deviation of plus/minus .1 percent, so that's at most the simulated plan have the maximum deviation of plus/minus .1 percent.

Q. Do you know in terms of real people what plus or minus .1 percent is?

A. Yes, that's a good question. Yes. So the choice of this is based on the fact that I'm working with precinct-level data, so precinct-level data is, you know, on average I think maybe 2,000 population or something along those lines, and plus/minus 1 percent is usually between 700 to 800 people in Kentucky.

Q. And it's plus or minus .1 percent, right?

A. Plus/minus .1 percent, yes.

Q. And why not require your algorithm to require

absolute equality among the districts?

A. Right. So in the -- you know, when the states -- many states enact their congressional plan, they often go down to one person difference. So the population based on the census is different from another district at most one or two people. Okay. However, for simulation analysis, which is designed to evaluate the characteristics. It's not designed to generate the plan that someone can pick and enact. Because we are based -- working on the precinct-level data, we don't have ability to go down to one person, right. So one person would require census block level data for which election results are not available.

So the fact that we use, as in many parts of analysis in academic literature, we use precinct-level data, and for that the .1 percent is appropriate deviation because, you know, going down to one person is not possible just datawise.

Q. Did you also include a compactness criteria, an algorithm, for purposes of the congressional map?

A. Yes. Generally these algorithm are designed to

generate compact districts because if you think about, you know, all possible districts, then you'd have many snake-looking districts that would we not care, so we focus on -- these algorithms are designed to generate relatively compact districts.

Q. And Mr. Trende's rebuttal report indicates that you used a compactness parameter of 1; is that right?

A. That's correct.

Q. And he thought that maybe a map drawer would choose .5 or 2 as opposed to 1 as a compactness measure.

Do you have any reaction to that?

A. So map drawers should not be use an algorithm to generate an enacted plan, so they should never choose a parameter, but if the point is to say more realistic choice is the compactness parameter should be .5 or 2, that's inaccurate because I've analyzed many other states as part of my academic research and part of expert witness work, but you never choose those extreme values. That would be really pushing the algorithm too far to, you know, keep these theoretical guarantees that I describe that are

very important part of the algorithm. So typically we may change like 1.1, 1.05, .97, .95 to make it a little bit more compact or a little bit less compact, but never the range of .5 or 2 that's suggested by Mr. Trende.

Q. And did you feed any criteria relating to county splits into the algorithm for purposes of evaluating the congressional map?

A. Yes, I did.

Q. Can you describe those for us.

A. Yes. So I made sure that the simulated plans have fewer than the number of counties that are being split under the enacted plan.

Q. And again, did you use any partisan criteria as part of the criteria for the algorithm?

A. No. And I should also note that each county is split, you know, at most once because that's an important part of the criteria, so the simulation -- I instructed the simulation algorithm to just do that.

Q. And did you use any racial criteria as part of the algorithm?

A. No.

Q. How many simulated plans did you generate for purposes of evaluating the congressional map?

A. 10,000. And that choice is just motivated by statistical efficiency. If you have 10,000, that's actually way more sufficient to yield accurate conclusions. You know, obviously, I could generate more, but that's [unintelligible].

Q. When you're generating the simulated plans, is it possible to freeze a particular district, in other words, to lock in one district and then simulate the remainder?

A. Yes, that's possible.

Q. And is that something that you would recommend doing in evaluating a map, using the simulation algorithms?

A. Depends on the context, so, for example, you know, in some cases where a particular district boundary is at dispute. So, you know, if you have, say, two districts and the boundary between those two districts is in dispute, then you could freeze the rest of the state and then generate those two districts to see how unusual those boundaries are.

Q. If you were trying to measure the compactness of an enacted plan, what impact would freezing a particular district have?

A. Right. So that you have to be careful because freezing one district will basically freeze that district boundary surrounding it, so that has an impact on compactness of the surrounding district. And so the conclusion has to be, you know -- you have to be very careful, right, because freezing that one district would have an impact on compactness of other districts that are neighboring with the frozen district.

Q. Did you consider Kentucky's historical congressional maps in developing your algorithm?

A. No.

Q. And why not?

A. So typically, when I evaluate the partisan bias of the enacted plan, I do not bring in the previous maps. The reason is that we don't know what went into the previous map, what factors were considered to create the previous maps. And so one of the important aspect of simulation algorithm is transparency. So, you know, you specify a set of criteria and under that criteria, the algorithm will generate the plans.

So when you -- if you input the previous plan, whatever the consideration that was used to generate that plan would affect the

results and may bias my conclusion in one way or another. So if I evaluate the partisan, you know, bias of enacted plan, I don't use the previous maps.

Q. And Kentucky currently has one Democratic representative and five Republican representatives in the US Congress. Why not add a criteria to your algorithm that would ensure at least one Democratic representative from Kentucky?

A. Because that would bias my conclusion. That would be sort of encouraging partisan gerrymandering. So I -- you know, in order to evaluate the partisan bias, you don't use partisan information. That would be a bad idea.

Q. And you focused your analysis of the congressional map on Franklin county, right?

A. Yes.

Q. Why did you do that?

A. Franklin county is notable because it's part of this District 1 that travels from the west side of the state all the way to the center of the state, and Franklin county is, you know, an important part of that district in dispute.

ATTORNEY HINKLE: I don't seek to

introduce this map to this witness, but I want the Court to be aware that we have included maps of the districts in the front of your binders, if you'd like to look at that.

If it's all right, Your Honor, I would like to give the witness one of those as well to reference as needed.

BY ATTORNEY HINKLE:

Q. Is that the enacted congressional map?

A. That's correct.

Q. So what was the first step in your analysis of looking at the enacted congressional map?

A. Right. So the first step of analysis was to evaluate the compactness of this district.

Q. And how did you do that?

A. Well, so, you know, one could look at it and then see it's not compact, but because I'm a simulation expert, what I do is I'm going to compare the compactness of District 1 under the enacted plan with simulated plans and compactness of the district that contains Franklin county under the simulated plan. And you never know, like, this shape may be necessary in order to comply with, you know, population and other criteria, so you always

want to be able to -- you know, you want to be able to compare this with the simulated plan that comply with all these other set of requirement and then see if this is an outlier.

Q. And did you use the full set of 10,000 simulated plans to do this analysis?

A. No. I substituted to the 93 percent of the simulated plans, so most of it, but -- which did not split Franklin county.

Q. And why did you make that choice?

A. Because the enacted plan does not split Franklin county, and I wanted to make sure that, you know, I'm comparing apples and orange -- apples instead of comparing to a different -- completely different districts.

Q. And you compared the compactness of the enacted first district with those in your simulated plan, right?

A. That's right.

Q. What compactness measure did you use?

A. So I used the measure called Polsby-Popper compactness score with is one of the very standard metric of compactness measure. I also used the Reock measure which is related measure that's, again, used in academic literature.

Q. And is your analysis of the compactness of the first district reflected in Figure 6 of your report on page 17?

A. That's correct.

Q. And can you describe for us what this shows.

A. Right. So this figure shows, again, the compactness of enacted plan, which is the red line, and compactness of the district that contains Franklin county as a whole, which is shown as a histogram, the gray bars. And the Polsby-Popper compactness score is the larger the value is, the more compact it is. So if the value is smaller, that means less compact.

And as you can see, almost all the simulated plans generate the district that contains Franklin county as a whole, that is much more compact than the District 1 of the enacted plan. In fact, more than 99 percent of the simulated plans generate the corresponding district that is more compact than the District 1 of the enacted plan which led me to conclude that District 1 is outlier in terms of the lack of compactness of that -- of that shape.

Q. So you're measuring the compactness looking just

at District 1, right?

A. That's right.

Q. Does the compactness of one district affect other districts?

A. Yes.

Q. In other words, is there necessarily a trade-off in the compactness if you change the compactness level of one district versus another?

A. I see. So compactness of one district affects the compactness of the other districts. Because if you change the district boundaries of one district, you know, the district boundaries of the surrounding districts have to change and then that will also lead to the change in other districts. So in a sense, they're all related. However, there's no general trade-off between -- like if you make one district more compact, you have to make another district less compact or vice versa. In fact, you can create a map that all the districts are not compact. You can imagine, just like make a lot of snakes, and that will lead to the map that has many, many districts that are not compact.

So they are related, but there's no general trade-off. In fact, what the simulation

shows it is possible to create -- because this simulation actually made sure that the average compactness level is the same as enacted plan. So my simulated plan on average, average across districts, have the same compactness level as enacted plan, right, but the enacted plan creates this District 1 that's highly non-compact.

What the simulation did shows that even if you keep the overall compactness, average compactness the same, I don't need to create this highly non-compact district. I can create the district that are much more compact across the board, you know, on average basically.

Q. So if you made the first district in Kentucky's map more compact, does that necessarily mean that the other districts become less compact?

A. No. And that's exactly what the simulation shows, right. So it's possible to make District 1 more compact without changing the overall level of compactness of the map.

Q. Dr. Voss's rebuttal report suggests that your relaxed -- as he describes it a relaxed standard for population equality caused your simulation to produce more compact maps.

You've described for us why you use the population measure that you did, but could you -- could you tell us what you did, if anything, to investigate Dr. Voss's critique in this regard.

A. Yes. So the Dr. Voss critique on my choice of population deviation, which is .1 percent, about 700 to 800 people difference across -- from the ideal target population, was puzzling to me because in his report, he says, you know, this choice is too big, so the .1 percent is too large, but as I explained, if you're using the precinct-level data, which is the analysis that I'm conducting, then the .1 percent, 700 to 800 people, is an appropriate choice because the precinct is not as small as the census blocks.

And he says that in the report he chose -- you know, he pinched, he reduced that population deviation, but then he cites number .001, which is .1 percent, which is exactly what I did, right. So that was puzzling to me because he's saying that, well, I picked too big a number and he says I -- you know, he set it to .001, but that's exactly the same number that I chose, so I was a little confused.

But then when I looked at his code, he actually set it to .00001 which is basically .001 percent or seven or eight people. So instead of choosing 700, 800 people, which I did, because of the size of the precinct, he chose -- in the alternative analysis he conducted in his report, he chose .001 percent which is seven to eight person -- people.

Q. And can you describe for us the impact that choice has on the algorithm.

A. Right. So first of all, that's not appropriate choice because precincts are much bigger. Precincts are not the size of seven, eight, six, five people. On average I think a couple thousand people. So if you set the tolerance -- population tolerance to that low, there are so few precincts that you would be able to move to generate the plans.

And so when I rerun his algorithm, the software that I wrote generates lots of warning, basically says this is not a good choice and it has some potential impact on the theoretical properties of the algorithm because you are choosing too tight of population threshold given the dataset that you are analyzing. And so

that's one concern, so that any results that might come out from such a tight population threshold, when the data itself is precinct-level data, there may not be mathematical guarantee that make these algorithms so attractive and powerful.

In addition, when I actually run this, right, even though with the warnings, you still get -- generate 10,000 plans. And I look -- I recreated the figures that are in my report using those output, there's no material difference.

So this is again -- what's important is to look at the distribution of the plan as a whole. So you cannot just choose one particular plan out of 10,000 and draw some general conclusions. In order to draw general conclusions, you need to look at the entire simulated output, and when you do that, the population deviation, based on his choice, has no material impact on the conclusions that I show.

Q. And did you do anything to analyze the partisan bias in Kentucky's congressional map?

A. Yes, I did.

Q. And can you describe for us what you did to do that.

A. Right. So for this analysis, I looked at the Democratic vote share of the districts that contain Franklin county, so that's basically for the enacted plan that's District 1.

Q. And is your analysis in this regard reflected in Figure 7 on page 18 of your report?

A. That's right.

Q. And can you please describe for us what this Figure 7 shows.

A. Right. So Figure 7, just like previous figures, focus on the districts that contain Franklin county as a whole. So under the enacted plan, this would be District 1. And District 1 on the enacted plan has, you know, Democratic share of votes around 35 percent. And the gray histogram basically shows what would be the Democratic vote share of this corresponding district under the simulated plan. And what you see here is that under simulated plan, Franklin county belong to the district that is much more Democratic so compared to the enacted plan. So enacted plan is basically making Franklin county a part of much more Republican-leaning district

in comparison to the simulated plans.

Q. And is your observation shown in Figure 7, is that statistically significant?

A. Yes. Again, it's more than 99 percent of the plans have higher Democratic vote share for the corresponding district than enacted plan, so I would say this is statistical [unintelligible].

Q. And is your opinion with regard to the partisan impact of the enacted plan dependent on your observations with respect to compactness of the enacted congressional plan, or are these separate?

A. They're separate conclusions. You know, obviously they're related because the way that District 1 is constructed is this -- you know, combining the highly Republican-leaning counties with Democratic-leaning counties to make additional Republican district.

Q. Are you giving an opinion today that Franklin county should be in a district that's represented by a Democratic representative?

A. No.

Q. When you were developing the criteria for your algorithm, were you attempting to create a map that might elect two Democratic representatives

from Kentucky?

A. No. Because my goal is to evaluate the partisan bias of the plans, so I do not use partisan information as input into my algorithm.

ATTORNEY HINKLE: If you can give me a minute.

THE COURT: Are we at a good breaking point for lunch?

ATTORNEY HINKLE: I think we are. We are, Your Honor. Thank you.

THE COURT: Okay.

UNIDENTIFIED COUNSEL: Your Honor, may I ask if Mr. Imai's examination is concluded, or do you have further questions?

THE COURT: No. She's got further questions. I just want to go to lunch.

UNIDENTIFIED COUNSEL: I understand that. I thought maybe she was done.

ATTORNEY HINKLE: Well, if you want to give me a minute to confer.

THE COURT: Yeah, why don't we see -- yeah, if you've got a couple more questions, that's all right.

ATTORNEY HINKLE: You know, I'd like to reserve the chance to ask a few more questions

after lunch, if I may.

THE COURT: That's fine. You all can talk over lunch. It looks like you're getting pretty close to the end.

ATTORNEY HINKLE: I am certainly very close.

THE COURT: All right. Usually I give an hour and 15 for lunch, so we will return at 1:30. Okay. 1:30. Thank you all.

You all need to talk to me about anything?

UNIDENTIFIED COUNSEL: We were just wondering if it's possible to do a slightly shorter break. I don't know how long cross-examination will last. Dr. Imai does have a plan to return to the airport tonight.

THE COURT: Why don't you just go down to Buffalo Trace and do a tour or something.

(Lunch Recess.)

THE COURT: We're on the record.

Okay. You're still under oath, Doctor. Okay. All right. You may continue.

ATTORNEY HINKLE: We have no further questions on direct exam.

THE COURT: Okay. No further

questions. Very good. All right. Very good.

CROSS-EXAMINATION

BY ATTORNEY BECKER:

Q. Good afternoon, Doctor. Heather Becker. I represent the Commonwealth.

I want to understand two points from your testimony. Using your ensemble in the vote share that you calculated, it's true that 76 of Kentucky's house districts lean in favor of Republicans, right?

A. I don't recall that exact number.

ATTORNEY BECKER: Can I use your box plot.

ATTORNEY HINKLE: Sure.

BY ATTORNEY BECKER:

Q. So again, looking at your chart, 76 of Kentucky's house districts lean in favor of the Republican Party, right?

A. That's a different -- you mean 76 out of 100?

Q. Yes.

A. That's not necessarily the case because -- should I explain the reason or --

Q. Sure.

A. So each of these box is a distribution of, you know, the district for -- that order of 76

doesn't mean like every single point -- you can already compare across districts, so it's possible that in the -- for a particular simulated plan, 78 or 74 of the districts are leaning towards one party or the other, so you'd want to calculate the actual number -- expected number of Democratic districts under the simulated plan, so that would be a different prop. This prop wouldn't necessarily tell you that.

Q. So right here --

A. Right.

Q. -- the average of your 76 ordered district falls -- the median falls below the 50 percent line.

A. Right.

Q. You would say that leans Republican.

A. So the average 76 -- I guess my question -- maybe I'm not understanding your question.

But average Democratic -- Democratic, you know, vote share of the average 76 simulated plan is, yes, 49 point whatever is there.

Q. And everything before it?

A. Well, that's -- everything before what? I just want to be careful about what I'm trying to --

being asked.

Q. This is your ensemble.

A. Right.

Q. The average of your ensemble districts would order at 76 leaning Republican.

A. Right. Among the -- all 76, you know, order districts among the simulated, the average vote share for that district is below 50 percent. Yes, that's right.

Q. And taking the average vote share of the district that contains Franklin county in your congressional simulation, the average Democratic vote share was 43 percent, right?

A. I don't memorize these numbers so I don't -- so this is congressional, not the house?

Q. Yes.

A. Okay. What was the question again? Sorry.

Q. When you look at the average vote share of the district that contains Franklin county in your congressional ensemble, it's 43 percent.

THE COURT: Talking about Republican votes, right?

ATTORNEY BECKER: He does it ordered by Democratic vote share, so it would be a 43 percent Democratic vote share.

THE WITNESS: 43 -- yeah. Okay.

Right. So 43.6 percent, you know, among the simulated plans that contain for -- for the district that contains Franklin county has a 43.6 percent average Democratic vote share, that's right.

BY ATTORNEY BECKER:

Q. So I think that's the bottom line of your report.

What I want to do now is talk about how you got there. So I want to make sure I understand.

Your ensemble for the house analysis contained 10,000 maps, right?

A. That's correct.

Q. And you generated a like number for your congressional analysis?

A. I generated 10,000 simulated plans for congressional analysis as well.

Q. And your algorithms could have made many different sets of 10,000, right?

A. Yes.

Q. Is 10,000 the universe of all the maps that could have been created?

A. No.

Q. You didn't look at any of the simulations in your ensemble, did you?
A. What do you mean look at?
Q. You didn't look at -- you didn't generate maps from your simulations. You didn't look at what they look like in real life.
A. I did. I did look at some of them.
Q. Before you received our reports?
A. Right. I mean, not all of them but some of them, yes.
Q. All right. For your work in this case, you used your redist software, correct?
A. That's correct.
Q. And does -- you call it R?
A. Yeah. R is the statistical programming language that redist is based on.
Q. Does R contain both your SMC and MCMC algorithms?
A. S -- what do you mean contain?
Q. Are they written into the R program?
A. It's part of the R package. Some parts are written in, you know, C program. Just it's faster.
Q. I don't want to go through it in great detail, but I would like to go through some of your code

with you. Okay?
A. Okay.
Q. Are you familiar with this code?
A. This is the congress? This is code for the congressional simulation.
Q. So this is the code you ran in R for your congressional simulation analysis?
A. Uh-huh.
ATTORNEY BECKER: For right now I'd like to mark it for identification as Exhibit 1.
(WHEREUPON, Commonwealth Exhibit 1 was marked for identification.)
BY ATTORNEY BECKER:
Q. Can you locate for me in this document where the algorithm you used to generate your analysis is?
A. So the algorithm is in the package, so this is the code that calls the algorithm.
Q. So your algorithm is not in here?
A. Yeah. The algorithm is in the package redist. So redist has a set of code that's, you know, contained in that package, and this code calls the redist.
Q. I'd like to look at the same document for your house analysis.
A. Okay.

Q. So is this the house analysis -- the house code analysis that you used?

A. Uh-huh.

ATTORNEY BECKER: I'd like to mark this for identification as Exhibit 2.

(WHEREUPON, Commonwealth Exhibit 2 was marked for identification.)

BY ATTORNEY BECKER:

Q. Can you locate in this document where your code is that you wrote for your analysis?

A. I'm not sure -- I'm not understanding your question.

Q. The code that you used to generate your simulation ensemble, where is it in this document?

A. Oh, simulate. Yes. So it's 03 -- 03 simulate SS [unintelligible] MS.

Q. And it goes on for 44 pages?

A. Well, depends on what you mean by -- it has all the prepping the data and setting the constraints, and all that is, you know, prior to actually coding the stimulation algorithm itself to generate the simulated plan, so there's that sort of prep part that has lots of lines of code in part because of the custom constraint code

that, you know, have to have county names and stuff.

Q. Is that pre-code located in the R package?

A. So this code is not a part of the package. This is the code that calls the R package function which has the algorithm program.

Q. Okay.

A. Does that make sense?

Q. I would also need to know what your R package said to know how to interpret this?

A. What do you mean by interpret?

Q. To be able to use this, I would also need to know your R code, right?

A. You need to be able to install the package and -- to run this, that's right.

Q. Well, let's look at your R code.

THE COURT: Heather, is the first one going to be Exhibit 1 and then 2 and then this is 3?

ATTORNEY BECKER: Well, as a matter of housekeeping, Judge, we do want to make sure that our binder is numbered as 1, what we did at the very beginning. So if we could do that as 1 and then I'll do the congress code as 2, house code as 3, and what Alex is handing you, the R

code, is 4.

THE COURT: Well, in your binder, where are they listed?

ATTORNEY BECKER: Those are not in our binder.

THE COURT: Gotcha.

ATTORNEY BECKER: Those are just the stipulated documents.

THE WITNESS: Gotcha. Gotcha. Gotcha. So the first one you handed me is 1.

UNIDENTIFIED FEMALE: No.

ATTORNEY BECKER: It would be 2.

THE COURT: 2.

UNIDENTIFIED FEMALE: The big binder is 1, the stipulated facts.

THE COURT: The stipulated facts is 1.

ATTORNEY BECKER: Right.

THE COURT: Now I'm understanding. 2, 3 and then 4.

ATTORNEY BECKER: 2 would be the one that says run congress; 3 would be the one that says run house; and then 4 will be the one that starts with the @RD name.

THE COURT: Gotcha. This one right here. I got them now. I'm going to put these

all in here.

(WHEREUPON, Commonwealth Exhibits 1, 2, 3 and 4 were marked and admitted into evidence.)

BY ATTORNEY BECKER:

Q. So I'm going to just mark that one as number 4.

So the document run is number 4. This is your -- this is your R code, correct, the R package software?

A. I think so. I mean, I assume you print out from the redist file. I mean, I don't memorize every line so, you know. Assuming that this is printed out from the actual package, yes.

Q. So once I have all three of these sets of code, I'm ready to start your simulation process. Yes?

A. You have to first, you know, install the package. The package is a set of programming files, so you have to, you know, download that and install. And once that's done, then, yes, the other R files can be used to generate simulated plans.

Q. And so that's roughly 11 files and 13 libraries in roughly 90 pages of code that I would need to have under my belt before I could start what you did?

A. Yes, but -- yeah. I mean, you have to have them, yes. Without them, it wouldn't be able to run, that's correct. But, you know, R itself has many, many files, so if you -- you know, if your definition is you have to have all these programs, then you have to have all the R -- all the code that's the backbone of R has to be printed out as well. That would be, you know, hundreds of files.

Q. So you say that you use R so that anyone can recreate your work.

A. That's correct.

Q. I would need an expert to tell me how to do what we just walked through. I might need you.

A. Yeah, but others can -- not just me, but others can also use it as well. So, yeah, you may need some expertise to use R and associated packages, but, yes, that's correct. You don't need me per se. You could have somebody else who is familiar with R and R packages.

Q. All right. You've never been appointed to draw a redistricting plan, have you?

A. No.

Q. I have a couple questions about some of the new analysis you unveiled today in your direct

testimony.

A. Sure.

Q. You reviewed Professor Voss's report. You reviewed Mr. Trende's report.

A. Uh-huh.

Q. When did you -- when did you form the opinions that you shared today?

A. This weekend, I think, after I received and reviewed the -- you know, the report and the code, associated code and data.

Q. Did you disclose your opinions to your counsel?

A. What do you mean by disclose?

ATTORNEY HINKLE: I'm just going to object to the extent your question is trying to invade our communications and work product.

ATTORNEY BECKER: Judge, I'm entitled to --

THE COURT: No, it's not really that. It's just when did you disclose. That's a typical question.

You can answer that question, Dr. Imai.

THE WITNESS: Okay. Yeah, I showed the results -- I share the results of the analysis with counsel.

BY ATTORNEY BECKER:

Q. When?
A. Oh, when. Sunday.
Q. Did you provide counsel with any of the underlying data for your conclusions?
A. I used the data received from -- from -- you know, for Dr. Voss and Dr. Trende -- Mr. Trende's analysis, so the counsel have those.
Q. I'd like to look at your c.v. really quickly.
A. Okay.
Q. Counsel on direct asked you about your publications.

How many of your publications relate to the work and analysis that you're doing here today?

A. Okay. Yes. Three of them relate very closely to what I'm doing today, but there are other -- there are other publications that are about simulation algorithms and, you know, general area of research, but three are specifically about redistricting simulation algorithms.
Q. I'd like to talk about some of your -- some of your report now.
A. Okay.

Q. So looking at your house analysis, you would agree that the input criteria that you choose are important to the outcome?
A. Yes, I do agree.
Q. And they have to be chosen carefully.
A. That's correct.
Q. And if you used additional or other criteria, that could change your conclusions.
A. That could, yes.
Q. So I want to look at page 7 of your report. Down here in paragraph 16, you have several bulleted points. These criteria, these are the constraints that you imposed in your simulations, right?
A. Right. I mean, in the -- the actual constraint itself is mathematical but described.
Q. So these are the criteria and then you assign constraint levels to the criteria?
A. Right. So this is my attempt of, you know, describing the constraints that I used.
Q. I think what you're talking about you described a little bit better on page 22. Can you turn to the appendix of your report.
A. Right. That's the details.
Q. So you say that you set county split constraint

at a level of 10.

A. Uh-huh.

Q. And you set a county multi split avoidance at a constraint of 7 and a custom constraint at a level of 10.

A. This is paragraph 11 on page 22?

Q. I'm sorry?

A. This is paragraph 11 on page 22?

Q. 10 and 11, yes.

A. Yes.

Q. What's the significance of a constraint of 7?

A. Do you mean statistical? I'm trying to understand your question.

Q. Sure. You chose a constraint of 7.

A. Uh-huh.

Q. If you -- no one told you to set it at 7.

A. Oh, I see.

Q. You picked 7.

A. Okay. Why did I choose 7? Is that --

Q. I guess two questions not asked compound.

You picked 7.

A. Right.

Q. And what would the difference have been if you picked 1 or 2 or 5?

A. Okay. I don't believe I tried those 1 to 5

specific numbers, but the general principle to choose this constraint is to, at least in this case, try to minimize the number of splits, whatever the constraint is trying to, you know, reduce to the extent that algorithm is actually capable of doing that.

So algorithm has multiple diagnostics that basically tells you whether -- you know, because if you make the constraint too strong, obviously there wouldn't be any plan or very small number of plans that would be able to satisfy that. So you -- you know, you reduce it to the point where algorithm is still performing well. And the other thing is that there are multiple constraints so you have to, you know, reduce each one of them to the extent that still the algorithm is performing well based on the general diagnostics that's available.

Q. So you wanted your algorithm to discourage multi splits, and you felt that a constraint of 7 would accomplish that?

A. Right. And to push it to below that, I felt that would start impacting the efficiency of the algorithm, so that's -- you know, that's the level I chose.

Q. And you didn't have any reason to believe that the Kentucky General Assembly was drawing its plan with constraint to avoid multi splits at a level of 7, did you?
A. No. So my -- yeah, no.
Q. And you said you didn't run it with a different constraint level.
A. I did run with different values. I didn't, you know, record every single one of them, but I settled on these values because I found that these values are still maintaining the efficiency of the algorithm while reducing these splits as much as possible.
Q. And did you include that criterion because plaintiffs' counsel told you to?
A. Which one?
Q. The multi split constraint.
A. Yeah, so the interpretation of the section 33 I relied on counsel.
Q. Do you have an independent understanding of what have Kentucky law requires?
A. No. I am not a lawyer.
Q. Have you ever read the case Jensen versus State Board of Election?
A. No.

Q. You had said that you tried different constraint levels and that the algorithm was running efficiently at 7.

What does the efficiency of the algorithm mean?

A. Right. So algorithm can stuck if you -- if you increase the strength of the constraint too much because then algorithm won't be able to find another plan that would satisfy that constraint. So in this Markov chain Monte Carlo and sequential Monte Carlo literature, there are a set of diagnostic techniques that one can use to make sure that algorithm are, you know, running efficiently.

Q. So I know what you told your algorithm to consider.

You didn't instruct your algorithm to consider race?

A. No.

Q. You didn't instruct your algorithm to consider communities of interest?

A. No.

Q. You didn't instruct your algorithm to consider where schools are?

A. No.

Q. You didn't instruct your algorithm to consider where churches are?
A. No.
Q. You didn't instruct your algorithm to consider where neighborhoods are?
A. No. Not to the extent --
Q. You didn't -- go ahead.
A. So no to the -- yeah. I didn't incorporate those factors directly, but that doesn't necessarily mean that those -- you know, say, for example, neighborhoods aren't kept together because, you know, to the extent the counties, for example, correspond to neighborhoods, and to that extent the simulated plans may have those characteristics, but I didn't directly tell algorithm keep these particular neighborhood together or, you know, churches or schools in certain districts, no.
Q. And you didn't instruct your algorithm to consider the location of county seats?
A. No.
Q. You didn't instruct your algorithm to consider the major transportation corridors in this state?
A. No.

Q. And you didn't instruct your algorithm to consider where natural boundaries are, like rivers or mountains?
A. No, but to the extent that they might coincide with, you know, county boundaries.
Q. County boundaries.
A. Yeah, that's right.
Q. And you didn't instruct your algorithm to consider where incumbents or candidates live?
A. No.
Q. And you didn't instruct your algorithm to consider or try to prevent double-bunking?
A. No.
Q. And you didn't instruct your algorithm to consider maintaining the continuity of representation?
A. No.
Q. And you didn't instruct your algorithm to consider core retention of districts?
A. No.
Q. So not a single one of the simulations in your ensemble considers any of the things we just talked about?
A. Not directly considers that.
Q. Wouldn't you agree, though, that those are all

well-established traditional redistricting criteria?

A. What do you mean by traditional redistricting criteria?

Q. That those are things courts have told us over time are reasonable for redistricters to consider when enacting a plan.

A. I don't want to say these are the set of traditional redistricting criteria.

Q. Sure.

A. I think in the academic literature, you know, things like population equality, compactness are considered as traditional redistricting criteria. Other things that you listed may or may not. I don't really wish to express opinion on exactly what counts as traditional redistricting criteria.

Q. You can say "I don't know."

A. Oh, okay. Okay. Well, I know about them, but I don't want to express opinions on whether they count as traditional redistricting criteria.

Q. At the end of your simulation analysis, or at least the first part of it, you conclude that House Bill 2 makes three additional splits to counties more than the average necessary in your

ensemble.

I'm looking at the chart on page 9 of your report.

A. Right. Okay.

You mean video 1?

Q. Yes.

A. Okay. Right. So an average simulated plan has, you know, 15 and enacted plan is 18 so [unintelligible].

Q. I want to move on to the next step of your analysis.

You then went on to calculate the partisan vote share. You said you used six -- six statewide races from 2019 in Kentucky and two 2016 federal statewide races.

How did you weight those races?

A. Equally.

Q. So each of the six constitutional office races are given the same weight. So is it a one-to-one, or did you --

A. One-to-one.

Q. The presidential and US Senate race, those are both statewide races.

A. Uh-huh.

Q. Are state legislative raises statewide races?

A. No.
Q. Are presidential races and US Senate races good predictors for legislative races, state legislative races?
A. I haven't done analysis of Kentucky, you know, election forecasting so I don't know.
Q. So it's not your expert opinion that those races are good predictions because you couldn't form that opinion.
A. I use them as a measure of partisan -- you know, partisanship at the precinct level as standards in the academic literature.
Q. So by selecting those races, you're assuming that voting patterns and voting history don't change, right?
A. No.
Q. So someone who votes one way in a presidential race you assume votes the same in a senate race, the same in all six constitutional office races?
A. No, I don't make that assumption. I'm using them as a measure of partisanship at the precinct level. It has nothing to do with their voting prediction of voting behavior.
Q. But you would agree that voter preferences do change.

A. Yes. Yes, they could change.
Q. And that the candidate quality could really impact turnout or support for a particular candidate.
A. Sure.
Q. But you didn't consider candidate quality when you were selecting your races.
A. So I used all the statewide elections for which I have the precinct-level results, so I did not consider candidate calculations.
Q. So you didn't consider the pertinent races when you were picking those particular returns to look at?
A. No.
Q. And specifically with your -- the selected state races that you chose, you didn't do anything to account for the clear outlier of the gubernatorial race, did you?
A. No. That's a point of combining multiple races. You don't want to rely on a particular race, and so by averaging all the different races, you try to get good measure of partisanship.
Q. But you certainly noticed that for all of the other five state constitutional offices, Republican candidates won handedly.

A. I actually didn't even consult with one. I took those election results and took the average, and this is standard practice.
Q. So the races you chose didn't contemplate at all that Matt Bevin ran a terrible campaign?
A. Nope, I didn't do that.
THE COURT: Is that one of y'all's stipulated facts?
UNIDENTIFIED COUNSEL: We'll stipulate to that.
BY ATTORNEY BECKER:
Q. But when you included Andy Beshear's vote share in your calculation, you didn't consider that Matt Bevin said that teachers kill kids?
A. No, I didn't even know about that, so...
Q. And you didn't know that he called teachers thugs?
A. No.
Q. You didn't know that he had threatened the northern Kentucky population with a toll bridge?
A. No.
Q. And you didn't know that he removed expanded public assistance to the commonwealth?
A. No.
Q. You didn't know that large populations of the

Republican Party disliked Matt Bevin?

A. No, I didn't know that.

Q. So you didn't account for any of that when you included Andy Beshear's high Democratic vote share in your calculation?

A. No. So taking the, you know, average so that you try to get general measure of partisanship not specific to any candidate or any race.

Q. I want to look back at -- we can look up here if you'd like, but this is on page 11 of your report.

When you were characterizing where the Democratic lean versus the Republican lean breaks, you used the flat 50 line as the line of demarcation for that, right?

A. Yeah. That's right.

Q. But you don't have any reason to believe that the statewide average vote share of Democrats at 50 percent is when Democrats in legislative races actually start winning races?

A. Right. So this is -- it's -- you know, it's just an average vote share across multiple elections that I looked at. So this is not a prediction of what might happen in the next election. This is just measure of, you know,

partisan lean for one way or another.

Q. Well, I think what you said earlier was that you highlighted these particular elections because they were the competitive ones. That suggests that the 50 percent line is important.

A. Right. I mean, you want to identify -- you know, it is a measure of partisanship, so when the measure is close to 50/50, those are the districts that tend to be competitive in the actual elections as well.

Q. But you have no reason to believe that that's actually true in Kentucky.

A. Well, you know, general tendency in many states is that these type of averaging past election results tend to correlate with the, you know, future election just to the extent that past election is correlated with future election.

Q. I'm talking about Kentucky.

A. Even Kentucky, but I haven't done an analysis to that sense, right. I don't have specific analysis to show you that.

Q. And if the threshold that is appropriate is somewhere closer to 51, 52, or 53 percent, would that change your analysis?

A. Well, it may change the -- well, it doesn't

really change the analysis. The fact that those D 76 to D 79 is an outlier, that fact is not changed. It doesn't matter how dotted line moves up and down, but the fact that those -- D 76 to D 79 red dots are below the simulated plan, Democratic vote share, that fact won't change. In fact, the simulated -- you know, that box plot one and dots won't change. What's going to change is just the dotted line going up and down.

Q. So D 76 is not an outlier and D 77 is not an outlier.

A. Okay. Well, sorry. I'm just doing the visual inspection here, but -- yeah. Anyway, that -- the D 76 and D 77, you know, whether you call this outlier or not, the vast majority of simulated plans have higher than [unintelligible] vote share for those districts so that fact won't change.

Q. But it also wouldn't change that you're predicting or guessing, based off your vote share, that the ordered District 76 and below are clearly Republican districts.

A. Yes. So each election may have some swings, right. As you all know, you know, some

elections Democrats do better and other elections Republicans do better, but what's important is the relative difference between the red dots and the box plot, and that won't change even if there's a uniform swing.

Q. But if the dotted line moves to 51 percent median, District 77 and 78 are below that relevant line.

A. Right. If the dotted line moves to, you know, 52 percent and, yes, those red line -- red dots become below the dotted line, but what I'm saying is the fact that the enacted plan systematically deviates from the simulated plan, that fact won't change. Because remember the simulation doesn't use election results at all, so it's the -- you know, when you evaluate, that's when the election results come in.

Q. Do you know how many seats Republicans currently hold?

A. In the house?

Q. Yes.

A. I don't remember exactly.

Q. Do you know how many votes are needed to override a veto?

A. I don't remember exactly.

Q. Do you know how many votes are needed to pass a bill?

A. I don't want to rely on my -- yeah, I don't remember exactly, so...

ATTORNEY BECKER: I need to do a little bit of setup.

THE COURT: I'm glad to see you all have color copies because, you know, I told you we don't have color copiers in the judiciary.

UNIDENTIFIED COUNSEL: You still don't have that copier, Judge?

THE COURT: I even asked for one. I did.

(Discussion held off the record.)

BY ATTORNEY BECKER:

Q. So in your opinion summary, you say that there are districts in Jefferson and Fayette county that improperly adjoin Republican precincts to make seats safer, right? You focus in on Districts 33, 48, 88, and 45. I'm on page 13 of your report, the beginning of 13.

A. Yes. I focus on, yeah, 33 and 48 in Jefferson, and I mention a couple other districts as well.

THE COURT: It looks like 48 needs to go into Oldham also. Am I reading that right?

ATTORNEY BECKER: So that is my point.

THE COURT: And the 33 looks like it used to go into Oldham, just not as much. Or more -- 33's more into Oldham, right, now under the new plan?

BY ATTORNEY BECKER:

Q. So Judge is beating me to the chase here, but I want to look at District 48.

So this is the old map. This is the map that was drawn in 2013, and so you can see District 48 here and District 48 over there. They make the same cut into Oldham county.

Are you aware that on the new map the only change here is one precinct?

A. No, I'm not aware.

Q. And Judge also noted that District 33 has always gone into Oldham county. And you see that here as well as over there?

A. Yes, I see that.

Q. And you understand that District 36 gained population, so this portion had to be taken up somewhere, and you see that that was done to District 33. And for the first time you understand Shelby county exceeded the population of an ideal district and it had to shed

population.

A. Uh-huh.

ATTORNEY HINKLE: Are you asking him if he knows that or asking him to accept that?

ATTORNEY BECKER: I'm asking him if he knows that.

THE WITNESS: No.

BY ATTORNEY BECKER:

Q. And you see that part of Shelby county was attached to 33?

A. Yeah, I see that.

ATTORNEY BECKER: Can I use your Fayette county insert?

ATTORNEY HINKLE: Sure.

BY ATTORNEY BECKER:

Q. And so over here you said that District 88 has been made more Republican by adding Scott county.

Do you see how white shaded that portion of Scott county is?

A. Yes.

Q. It's not a large portion of Republican voters.

A. Oh, you mean on the right map?

Q. Yes.

A. Yeah. So that is showing that on average,

across simulated plan, those white areas would have belonged to more competitive districts. It's not showing that both Democrats and Republicans live there necessarily. It's showing that that particular area would have belonged to more competitive districts under the simulated plan.

Q. I want to look back at your c.v.

A. Okay.

Q. Prior to 2012, you had not offered expert testimony in any litigation.

A. Prior to 20 -- what year did you --

Q. 2021.

A. Oh, yes. Correct.

Q. And that includes partisan gerrymandering litigation?

A. Right. That's correct.

Q. Earlier, counsel asked you if you had ever declined a job, and you had indicated that you had. What jobs had you declined, beyond the one where you were already retained by the other side?

A. I was -- yeah. I was asked by the lawyers -- the counsel representing New York Democrats for the New York redistricting case

[unintelligible].

Q. And you had indicated that you declined that job because you didn't think they would be able to prove their case?

A. I didn't feel comfortable -- based on the analysis I've done myself, I didn't feel comfortable proceeding with that case, providing expert witness case in that.

Q. Had you declined any other jobs?

A. I'm trying to remember. I don't think so. I feel like I may have or I may not have. These are short conversations that happen and so I don't remember after that. So I may have, but not, like, often.

Q. Did you decline any work in the Maryland redistricting litigation?

A. I wasn't asked -- approached by anyone in the Maryland case.

Q. I want to talk about your algorithms now.

You introduced your MCMC algorithm in 2020, right?

A. Are you talking about the specific publication or --

Q. Yes. Is that the first publication where you introduced that algorithm?

A. So in academia, there's often a huge lag between when you have a paper and then, you know, there's [unintelligible], but the Journal of Computational and Graphical Statistics paper, I think that's what you're referring to. Is that what you're referring to? I'm just trying to make sure it's 2020, it's not some other years. Yeah, that's right.

So the Journal of Computational and Graphical Statistics, yeah, 2020 is the publication year, yes.

Q. Are you looking at number --

UNIDENTIFIED SPEAKER: [Unintelligible].

ATTORNEY BECKER: Oh, yeah, it's gone red.

THE COURT: What are you saying? We've never had that happen.

UNIDENTIFIED SPEAKER: I don't know if it's, like, overheating or [unintelligible] loud noise.

I can call Amy, if you want, or we can just pray it's recording.

THE COURT: Why don't you -- we'll just keep because it's -- the lights are still on.

Would you just step out and talk to Amy and see if she knows what it is. I've never had that beep happen in 23 years.

Okay. You can continue whenever you'd like.

ATTORNEY BECKER: I'm sorry, Judge. Did you say that we could go or no?

THE COURT: Well, let's just wait. Let's do this: Let's stop and wait. It might be better to wait and talk to Amy.

(Brief Recess.)

THE COURT: Okay. You may continue.

ATTORNEY BECKER: Does it matter that it's still red?

UNIDENTIFIED SPEAKER: We want it to be red.

ATTORNEY BECKER: Oh, you want it to be red. Okay.

UNIDENTIFIED SPEAKER: If it's yellow it's bad or flashing.

BY ATTORNEY BECKER:

Q. I think when we stopped we were talking about -- on your c.v., page 4, the article you have cited is number 12. We were talking about that as the first article where you introduced

your MCMC algorithm in 2020.

A. That's right.

Q. And that wasn't the only article you wrote about the MCMC algorithm you were working on. You wrote another one, right?

A. Yes.

Q. I'd like to hand you a copy of that.

ATTORNEY BECKER: And, Judge, I think we're on Commonwealth Exhibit 5.

THE COURT: Uh-huh, that's the one you're on.

(WHEREUPON, Commonwealth Exhibit 5 was marked for identification.)

BY ATTORNEY BECKER:

Q. Professor, are you familiar with this article?

A. Yes.

Q. Did you write this article?

A. Yes. Yes, with collaborators.

Q. I'm sorry.

A. With collaborators. Yes.

Q. And it was published in the Journal of Computational and Graphical Statistics?

A. That's correct.

Q. And it was published in 2020, sometime early in that year?

A. I don't know exactly when, you know, it was -- yeah. I don't know exactly when it was published, like during that year.

ATTORNEY BECKER: I'd like to admit this as an exhibit, please.

THE COURT: How about we go ahead and admit 1, 2, 3, 4, and 5 right now.

Is there any objection, Michael, to any of those, or Casey?

ATTORNEY HINKLE: No, Your Honor.

THE COURT: Okay.

(WHEREUPON, Commonwealth Exhibit 5 was marked for identification.)

(WHEREUPON, Commonwealth Exhibits 1, 2, 3, 4, and 5 were admitted into evidence.)

BY ATTORNEY BECKER:

Q. And then as you continued to work on this algorithm, you authored a second article, correct?

A. Yes. I've written multiple papers.

Q. But on this particular topic, the next article you wrote was what you have at number 13, another 2020 article?

A. Yes, that's -- that's correct.

Q. Are you familiar with this article?

A. Yes.
Q. You wrote this article?
A. Yes.
Q. And it was published in the Journal of Statistics and Public Policy?
A. That's correct.
Q. In 2020?
A. That's correct.

ATTORNEY BECKER: Move to admit this as Commonwealth Exhibit 6.

THE COURT: Okay. Any objection?

ATTORNEY HINKLE: No, Your Honor.

THE COURT: Okay. It's admitted.

(WHEREUPON, Commonwealth Exhibit 6 was marked and admitted into evidence.)

BY ATTORNEY BECKER:
Q. I notice that you wrote this article, as well as the one before, with a gentleman by the name of Benjamin Fifield.
A. Yes.
Q. What does he do now?
A. He's a data analyst for ACLU.
Q. And these papers were peer-reviewed?
A. That's correct.
Q. And they were approved for publication?

A. That's correct.
Q. Did you introduce your SMC algorithm in 2021?
A. 2020.
Q. 2020 was the first draft?
A. Well, yes. So these papers, you know, takes time to appear in print, so the publication date does not necessarily correspond to when the method was developed.
Q. I want to make sure you heard my question. I asked about your SMC algorithm.
A. Right. SMC, I think the first draft was 2020.
Q. Okay. I'd like to hand you a copy of your working paper --
A. Okay.
Q. -- for that algorithm.
A. Okay.
Q. So this document says -- are you familiar with this document?
A. Yes.
Q. Did you write this?
A. Yes.
Q. And your first draft was in 2020?
A. That's correct.
Q. And it says this draft August 10, 2021?
A. That's correct.

Q. Was this article published in a journal?
A. It's in the review process.
Q. So it's in the peer-review process?
A. That's correct.
Q. So this is a working paper?
A. That's correct.

ATTORNEY BECKER: I'd like to move to admit this as Commonwealth Exhibit 7.

THE COURT: Okay. Do you have any objection?

ATTORNEY HINKLE: No.

THE COURT: Okay.

(WHEREUPON, Commonwealth Exhibit 7 was marked and admitted into evidence.)

BY ATTORNEY BECKER:
Q. I want to talk about some of your statements in this working paper.

I'm looking on the first page in the abstract.

A. Okay.
Q. Where it says "For successful application" -- I'm going to read it to you. It says:

"For successful application, sampling methods must scale to large

maps with many districts, incorporate realistic legal constraints, and accurately and efficiently sample from a selected target distribution. Unfortunately, most existing methods struggle in at least one of these areas."

What existing methods were you talking about?

A. This is a general statement so it's not specific to a particular algorithm, per se.

Q. But you wrote this paper to address concerns with the MCMC algorithms that were prevailing at the time, right?

A. That's correct.

Q. And so you're saying here that your MCMC algorithm cannot in actuality sample from a specific target distribution.

A. I didn't say that.

Q. You say it suffers from one of these weaknesses, correct?

A. Yes, but that's different from saying cannot sample. So it's -- in the context of academic research, we always try to improve the existing algorithms, and, you know, that's -- that's the

context. You always want to, you know, improve what's out there. That's why we do research.

Q. I want to read not the next sentence but the one after. You write:

"Because it samples directly, the SMC algorithm can efficiently explore the relevant space of redistricting plans better than the existing Markov chain Monte Carlo, MCMC, algorithms that yield dependent samples."

Is that a true statement?

A. The statement is true, but it's not -- it's all relative. Right, we're trying to improve the performance of the existing algorithms.

Q. If you can turn with me to the second page. I'm looking at the fifth full paragraph.

A. Page 1 or page 2?

Q. It's labeled as page 1, but it's the second page of the document.

A. Okay.

Q. You say:

"MCMC algorithms can in theory sample from a specific target distribution and incorporate

constraints through the use of an energy function. In practice, however, existing algorithms struggle to mix and traverse through a highly complex space, making scalability difficult and accuracy hard to prove.

"Some of these algorithms make proposals by flipping precincts at the boundary of existing districts and rendering it difficult to transition between points in the state space, especially as more constraints are imposed."

Did I read that accurately?

A. I think you did.

Q. Now, the articles that you cite parenthetically here, do you cite your own article in both of those statements?

A. Yeah. I'm trying to improve myself too, so...

Q. Can you turn with me to numbered page 3.

THE COURT: Did you say page 3?

ATTORNEY BECKER: Yes.

BY ATTORNEY BECKER:

Q. About midway through this page, you refer to another expert in your field Wendy Tam Cho and

her criticisms of the existing MCMC algorithms, and in response you write the third full paragraph. I'm going to read just a portion of it.

> "First, the distributions that some of these algorithms sample from are not made explicit, leaving open the possibility that the generated ensemble is systematically different from the true set of all valid plans. Second, even when the distribution is known, the MCMC algorithms used to sample from it may be prohibitively slow to mix and cannot yield a representative sample."
>
> Did I read that correctly?

A. Yes, you did.

Q. Will you turn with me to page 13 of this article. I'm not going to read all of this page, but what I would like to ask you is a question that summarizes what's going on here.

So what I read on this page is that at least two separate points your MCMC algorithm failed to yield reliable results, correct?

A. What do you mean by your MCMC algorithm?

Q. So throughout this article, where you're citing back to yourself, you call the comparison the state of the art MCMC algorithm, and in the second paragraph on page 13 you say:

"The upper panel of Figure 4a shows the resulting density estimates. While the target distribution is highly multimodal, there is a good agreement between the SMC sample and the reference distribution. In contrast, the MCMC samples fail to accurately capture the left tail of the distribution and oversample certain values of the right tail."

Does it say that?

A. Yeah. So this MCMC algorithm that I used in this article is not the same as the one I developed, so it's something that's different, by a different author, but, you know, these are comparisons of -- you know, in the academic article, you know, validation exercises to see how challenging problems can be addressed, you know, efficiently by one method over another.

Q. The last sentence on this page reads:

"In comparison, the MCMC algorithm

was not able to sample accurately from this target distribution in 20,000 iterations."

Did I read that correctly?

A. Yes, but this is not a general statement. So in this particular example that are actually somewhat contrived because here, in these examples, you can actually enumerate the -- all possible ways, so you can actually -- you know, you know exact truth -- true distribution list, and it's a very challenging setup that we set these things up so that -- to see how these different algorithms perform in these specific applications. So I don't want to take this sentence out of context and, you know, make it into a general statement.

Q. I want to look on page 14. It says in the first paragraph, four lines down, you write:

"Since the merge-split MCMC algorithm is not specifically designed to enforce this hard constraint, we do not present its results."

In this paragraph where you're not presenting the results because the algorithm is

not designed to enforce the hard constraint, isn't the hard constraint the hard multi split constraint?

(Telephone ringing.)

A. Sorry. So the multi split constraint is not a hard constraint that I used in the Kentucky case. It's not a hard constraint.

So this hard constraint I'm talking about in this article is just a total number of times being split. So in SMC, you can actually turn that into hard constraints so that no simulated plans have, you know, more than certain number of counties that are being split, but multi split constraint is actually a soft constraint that I used.

THE COURT: Jill, I used to fine people $50 and give it to your domestic violence group. Do you remember that?

JILL: Do you want me to pay that right now?

Yeah, I do.

THE COURT: Sorry, Heather.

BY ATTORNEY BECKER:

Q. One final question. Can you turn with me to page 15.

A. Okay.

Q. I'm looking at the last sentence of the section that's on this page. It says:

"This implies that SMC is several times more effective than the state-of-the-art MCMC algorithm in terms of runtime per effective sample. Although Additional study is warranted, our results suggest that the proposed algorithm may be substantially more effective when applied to real-world redistricting problems."

Did I read that accurately?

A. Yes, you did.

Q. You stand by all the statements that you made in this working paper?

A. I do.

Q. But you used your MCMC algorithm for your state house analysis?

A. Right. So again, which algorithm you use depends on, you know, what you're studying. So the reason why I used MCMC algorithm for the state case is that it better handles certain types of constraints when the number of district is large. And so the SMC -- because SMC builds

the one district at a time, as opposed to MCMC algorithm where you start with the redistricting, so the SMC is enabled to see, you know, certain types of constraints that requires you to know the -- the entire redistricting plan itself.

So, you know, again, these are sort of statement that's applicable to the particular applications I had in this specific paper, but, you know, again, I don't want to -- I don't want anyone to generalize this statement to any case out there in the world. You know, it has to be considered, both types of algorithms.

Q. I appreciate your explanation. I asked you if you used your MCMC algorithm to do your state house analysis. Yes or no?

A. I did use MCMC algorithm for the state house, yes.

Q. Okay. I want to go back really quickly and talk about specifically Districts 48 and 33 in the new map.

You would agree with me, Professor, that District 48 on that map is more compact than District 48 on this map, right?

A. It depends how you measure compactness.

Q. Just give it the eyeball test. We don't have your computer.
A. I'm a statistician. I don't really do the eyeball test.
Q. I want to talk about -- we talked earlier about population growth in District 36 and in District 58 and how that impacted District 33.

Are you familiar with the community of interest that this area covers?
A. I did not use community of interest in my simulation algorithm.
Q. That's not my question.

I'm asking if you're familiar with the community of interest --
A. No.
Q. -- in this area.

So you're not aware that there's a fire station district in pea 73 valley that crosses the county line?
A. No.
Q. And you're not aware that this area is called Pewee Valley and there's a women's prison that's actually located in Shelby county?
A. No.
Q. This area is intricately intertwined.

A. No.
Q. I want to go back to our discussion of Matt Bevin.
A. Okay.
Q. So this is the 2019 gubernatorial race. Now, we talked about all the things that you didn't know about him.

Did you know that that election was decided by less than 5,000 votes?

A. No.
Q. Did you know that the other five elections were decided by at least 100,000 vote difference?
A. No.
Q. Did you know that our secretary of state ran against a former Miss America -- she was like the winner, right? She won.
A. No, I had no idea.

THE COURT: Did you know that Matt Bevin attacked a very well-known judge here in Franklin county? During the break, I saw Phillip and he said to mention that.

ATTORNEY BECKER: I left that out of my list.

BY ATTORNEY BECKER:
Q. You would agree that an election that's won by

5,000 votes is an outlier compared to five other elections, at the same time, won by over 100,000 votes?

A. I mean, compared to those other elections, but, you know, many elections are close just in general.

Q. Okay. I want to switch topics and talk about your congressional analysis.

A. Okay.

Q. Your report only mentions Franklin county, right?

A. That's correct.

Q. But there are other counties that switched districts in the new congressional plan, right?

A. Right, but as I mentioned, I didn't consider the previous map so that's not part of the criteria.

Q. So you were told to focus on Franklin county.

A. What do you mean by told?

Q. You didn't look at the old map --

A. Right.

Q. -- but you acknowledge that other counties switched. Why focus in on Franklin county?

A. Oh, I see. Well, Franklin county is -- you know, if you look at District 1, it's the edge of this lengthy district that -- you know,

that's comprising that District 1, so it's -- you know, it's one place and upon instruction of counsel, that's the part that I focused upon.

Q. So you didn't focus on Franklin county because that's where the plaintiffs wanted to file suit?

A. Oh, I wasn't aware of who filed suit about, you know, where they're located or anything like that.

Q. Well, do you know the compactness measure for the other five districts in Senate Bill 3?

A. I did look at it at some point. I don't have it on top of my head.

Q. Do you know the compactness measure for the whole map?

A. Oh, yeah, I looked at that as well. I think that's in the report, in the appendix.

Yeah. So it's Figure 10. So that's overall compactness score average of the plan, so the red line is the enacted plan and histogram is the simulated plans. That's overall, not district by district.

Q. Do you think Figure 10 is the analysis of the whole plan?

A. Yeah, so this is overall -- yeah. So the Polsby-Popper is the average across districts,

and the other measure -- the other compactness measure is a plan-wide measure, so there's no specific district-level measures.

Q. So what I see here is that the enacted plan falls right within the average range of your simulation for compactness of the plan as a whole.

A. Right. So exactly that's the point. So on average I made sure that compactness of the simulated plan is similar to the enacted plan, so that's by design, but what I show is that even if you keep the overall level of compactness the same, District 1 is highly non-compact.

Q. But you don't know the compactness measures of the other five districts.

A. I did look at it at some point. I didn't include it in the figure, but I did look at the compactness of other districts as well. And if you take the average, it will be the red line, so some were more compact to offset the uncompactness of District 1.

Q. It's true, isn't it, that every other district is more compact over the last map?

A. Oh, again, I didn't look at the last map so I

don't know. I don't know the comparison.

Q. You only do a compactness measure using the Polsby-Popper method, right?

A. Yes. For this, but I also did the Reock which is actually more computational intensive. That's Figure 13. That's -- I did this only for District 15 -- I'm sorry -- District 1 in that Figure 13.

Q. Is the Polsby-Popper measure built into your SMC algorithm?

A. No. And neither Reock, this other measure that's in Figure 13 is not part of the algorithm.

Q. Have you ever heard of -- let me make sure I get the names right.

Have you ever heard of Nicholas Stephanopoulos and Eric McGhee?

A. Yes.

Q. Are they well respected experts in your field?

A. Yes. Nick is my colleague at Harvard Law School.

Q. So you don't want to say anything about bad your colleague here today?

A. He's a great scholar.

Q. Have you ever read their work, The Measure of a

Metric?

A. Yes, I've read that ever since he got the paper.

Q. So are you familiar with their statement in that article where they say "Scholars have not selected a gold standard among the metrics" -- he's talking about the measures of compactness -- "but, rather, have managed to use them productively in research by combining multiple measures and adjusting weights for each specific purpose"?

A. Well, I don't memorize what he wrote, but if he says that in the article, that's the statement he made.

Q. But you didn't use any other metric beyond primarily the Polsby-Popper and then Reock as a crosscheck? You didn't use any of the other standard available methods?

A. What other measures are you talking about?

Q. So there's the inverse convex hull, Schwartzberg method.

A. Okay.

Q. You didn't use either of those?

A. Yeah. No. The Polsby-Popper, to be fair, is the most commonly used method. Obviously, compactness can be measured in different ways.

Q. But the Polsby-Popper method does not like sharp curves.

A. Right. So different measurements try to capture different aspects of compactness. That's correct.

Q. So in a state where we have a lot of rivers that are windy and mountains that don't respect straight lines and bounded by a river, Polsby-Popper might not be the most favorable method to use.

A. Well, one could debate the appropriateness of different compactness measures, but one advantage of the simulation method is that, you know, because you're comparing -- it's difficult to say, well, because Polsby-Popper is .2, that's too low or too high, but one advantage the simulation method offers is that you're actually comparing with the other alternative plans using the same exact measure, so you're holding the measurement constant and then doing a comparison, accounting for all the geographical features and rules and other things.

So, you know, I do feel comfortable using the simulation method and doing the

comparison based on Polsby-Popper or some other measures whereas, you know, interpreting these numbers, as you pointed out, as it is might not be appropriate depending on the state.

Q. The vast majority, if not all of your congressional analysis, is premised on compactness. Yes?

A. Well, first half is compactness and the second half is, you know, partisanship.

Q. Can you tell me the balance of weight you gave to your population equality constraint versus the weight you gave to your compactness?

A. Oh, okay. In these algorithms, population constraint is a hard constraint. So when you specify it, the algorithm will generate the simulated plans that always satisfy the population constraint, so we never exceed that threshold whereas compactness is a relative measure; it's not a dichotomy.

Q. So when your algorithm is creating districts in each of your simulations, it is forced to follow your population constraint --

A. First, yes.

Q. -- but in doing so is guided by your compactness measure?

A. Yeah, that's one way to think about it. Another way to think about it is to consider a set of simulated plans that -- you know, simulated -- consider a set of alternative plans that satisfy population constraint and then among those consider compactness, you know, try to, say, select -- give more weight to more compact districts, for example.

Q. I want to talk about your population constraint.

A. Okay.

Q. You're aware that some congressional plans try to observe a strict one person deviation, right?

A. Yes, I'm aware.

Q. But you didn't adopt that requirement in this case.

A. That's correct.

Q. Are you aware that the enacted plan, Senate Bill 3, does just that; it's within one person equal population?

A. I think I've seen that at one point.

Q. But your constraint was a plus or minus .1 percent which I think I heard you say earlier is a spread of about 7 to 800 people?

A. That's right. That's maximum. So some plans are much lower than that, but that's the maximum

allowed deviation.

Q. You'd agree that when the law requires as near as practicable that one person is objectively better than 800?

A. I'm not a lawyer, but one person is smaller than 7 or 800.

Q. I want to go back to where we started.

A. Okay.

Q. You'd agree that if the vast majority of plans that are generated by your simulation method using what you call neutral redistricting criteria would produce the same seat share in the enacted plan, then the conclusion that there's a partisan bias is not supported.

ATTORNEY HINKLE: Objection to form. I'm sorry. I just didn't follow the question.

ATTORNEY BECKER: Sure.

BY ATTORNEY BECKER:

Q. So if the vast majority of the plans in your ensemble have the same basic seat share as the enacted plans, it's not -- it's not right to assume that there's been a partisan bias.

A. Well, it depends on what you mean by partisan bias, I suppose, right. That's, I guess, the whole difficult thing, but yeah.

Q. When we talked about your house conclusions, I think we decided -- we agreed that your simulations suggest that 76 districts should lean in favor of the Republican Party.

ATTORNEY HINKLE: Objection. It's inconsistent with prior testimony.

THE COURT: Okay. What's your objection again? I didn't hear you. I don't hear very good.

ATTORNEY HINKLE: I'm sorry. I think that's inconsistent with Dr. Imai's prior testimony. Of course, he can explain if it is or isn't.

THE COURT: Yeah, it's overruled.

I think your question was the 76 districts that are Republican.

ATTORNEY BECKER: Right, which I think we've established that.

THE COURT: Yeah, I think it's been established when you were pointing to the one map. So you can ask your question to him again.

ATTORNEY BECKER: Sure.

BY ATTORNEY BECKER:

Q. Isn't it true that under your simulation analysis, the Republican Party in Kentucky

should expect for 76 districts to lean in its favor?

A. Oh, I see what you're trying to ask. Okay.

So this is average vote share of -- Democratic average vote share. And if you -- are you thinking about the seat share, like how many seats the Republicans would win given an election?

Q. I know that you're not capable of rendering that opinion, so I'm just asking if your simulations suggest that 76 districts lean in favor of the Republican Party.

A. Oh, yeah. So that ordered 76th district, according to my simulation, on average lean towards Republican if you use the, you know, average vote share from the past elections that I used.

THE COURT: Well, the follow-up question to that: Is it 76 districts in the new plan, or are there more that lean Republican? Is that what your follow-up is?

ATTORNEY BECKER: I would just like to establish that using his own simulations and his data, that we all agree that 76 districts lean Republican.

THE COURT: Well, their question is does 81 or 83 add to the plan. Is there any way he has a prediction for that? Does that make any sense?

ATTORNEY BECKER: So I think what you're asking is he capable of predicting whether the Districts 77, 78, 79, or 80 go Republican in an actual election.

THE COURT: Or lean Republican in this new analysis. Where is the cutoff? Where is the 50/50? I was trying to figure that.

THE WITNESS: Right. So that really depends on each election, right. There's always, you know, swing from one election to another based on variety of factors, including candidate popularity and other factors.

So what I was establishing in Figure 3 is that the 76th district on the enacted plan is much more Republican-leaning than the vast majority of simulated 76 district.

THE COURT: Okay.

BY ATTORNEY BECKER:

Q. Question about your congressional analysis.

A. Okay.

Q. So on page 18, you say:

"Under these simulated congressional plans, the Democratic vote share for the district that contains Franklin county is 43.6 on average."

Correct?

A. That's correct.

Q. And if we're using a strict 50 line, that district is not likely to lean Democratic.

A. Again, this is, you know, a measure of partisanship based on the literally average of past election vote share. So, you know, I don't want this to be interpreted as like a prediction of the future election or anything like that. It's just a measure. In the past elections, 43 percent of voters voted for Democrat on average. But, yeah, it's less than 50 percent, if that's what you're --

Q. So using your simulation data, we should reasonably expect in the commonwealth to have a congressional delegation of five Republicans and one Democrat?

A. Again, I'm not expressing any opinion on likely, you know, number of Democrats or Republicans in future elections. I didn't do that analysis.

ATTORNEY BECKER: Judge, can I have a minute.

THE COURT: Yeah.

ATTORNEY BECKER: Judge, we'll pass the witness back.

THE COURT: Okay. Do you have any follow-up?

ATTORNEY HINKLE: It's very brief, Your Honor.

THE COURT: Okay.

REDIRECT EXAMINATION

BY ATTORNEY HINKLE:

Q. Dr. Imai, you were asked questions about use of the MCMC type of algorithm for purposes of analyzing the Kentucky state house map.

Are you confident that that was the right type of algorithm to use for the task to which you put the algorithm in this instance?

A. Yes, otherwise I wouldn't put in my report.

Q. And have you used the MCMC type of algorithm in any of your prior expert engagements?

A. Yes, I've done it before.

Q. And had produced reports on the basis of the MCMC algorithm or expressed opinions in court based on that type of algorithm?

A. Yes.
Q. And those opinions to your knowledge have been accepted by the courts?
A. Yes.
ATTORNEY HINKLE: Thank you, Your Honor. Nothing further.
THE COURT: Okay. Do you have any follow-up?
[No audible response heard.]
THE COURT: Okay. Can we release this witness? Are you okay to release him?
Okay. You can try to make your flight or you can go to Buffalo Trace and stand in line with everybody else. Thank you, Doctor. I appreciate you being here.
All right. Let's have the lawyers up here to talk about where we're at.
And also, Heather, you want to make these part of your exhibit? Are they in your book?
ATTORNEY BECKER: Well, they're in the book, yeah. I just thought it would be easier for y'all to look at those.
THE COURT: Okay. Good enough.
[End of requested transcription.]

R E P O R T E R' S C E R T I F I C A T E

STATE OF NORTH CAROLINA

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I, DENISE MYERS BYRD, Court Reporter/ Transcriptionist, CSR 8340, do hereby certify that the transcription of the recorded proceeding, testimony of KOSUKE IMAI, Ph.D., held on April 5, 2022, as indicated in the attached caption, was taken down by me stenographically to the best of my ability and thereafter transcribed under my supervision; and that the foregoing pages, inclusive, constitute a true and accurate transcription of said recording.

Signed this the 19th day of April 2022.

Denise Myers Byrd

Stenographic CSR 8240

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Exhibit 23

IN THE SUPREME COURT OF OHIO

Meryl Neiman, *et al.*, **League of Women Voters of Ohio, *et al.*, Petitioners,** **v.** **Secretary of State Frank LaRose, *et al.*,** **Respondents.**	**Case No. 2022-0298** **Case No. 2022-0303** ***Consolidated*** Original Action Filed Pursuant to Ohio Constitution, Article XIX, Section 3(A)

Expert Report of Sean P. Trende

I. Qualifications

Professional Experience:

I serve as Senior Elections Analyst for RealClearPolitics. I joined RealClearPolitics in January of 2009 after practicing law for eight years. I assumed a fulltime position with RealClearPolitics in March of 2010. RealClearPolitics is a company of around 50 employees, with its main offices in Washington D.C. It produces one of the most heavily trafficked political websites in the world, which serves as a one-stop shop for political analysis from all sides of the political spectrum and is recognized as a pioneer in the field of poll aggregation. It produces original content, including both data analysis and traditional reporting. It is routinely cited by the most influential voices in politics, including David Brooks of *The New York Times*, Brit Hume of Fox News, Michael Barone of The Almanac of American Politics, Paul Gigot of The Wall Street Journal, and Peter Beinart of The Atlantic.

My main responsibilities with RealClearPolitics consist of tracking, analyzing, and writing about elections. I collaborate in rating the competitiveness of Presidential, Senate, House, and gubernatorial races. As a part of carrying out these responsibilities, I have studied and written extensively about demographic trends in the country, exit poll data at the state and federal level, public opinion polling, and voter turnout and voting behavior. In particular, understanding the way that districts are drawn and how geography and demographics interact is crucial to predicting United States House of Representatives races, so much of my time is dedicated to that task.

Publications and Speaking Engagements:

I am currently a Visiting Scholar at the American Enterprise Institute, where my publications focus on the demographic and coalitional aspects of American Politics. I am also the author of *The Lost Majority: Why the Future of Government is up For Grabs and Who Will Take It*. In this book, I explore realignment theory. It argues that realignments are a poor concept that should be abandoned. As part of this analysis, I conducted a thorough analysis of demographic and political trends beginning in the 1920s and continuing through the modern times, noting the fluidity and fragility of the coalitions built by the major political parties and their candidates.

I also co-authored the 2014 Almanac of American Politics. The Almanac is considered the foundational text for understanding congressional districts and the representatives of those districts, as well as the dynamics in play behind the elections. PBS's Judy Woodruff described the book as "the oxygen of the political world," while NBC's Chuck Todd noted that "Real political

junkies get two Almanacs: one for the home and one for the office." My focus was researching the history of and writing descriptions for many of the newly-drawn districts, including tracing the history of how and why they were drawn the way that they were drawn. I was assigned South Carolina as one of my states. I have also authored a chapter in Larry Sabato's post-election compendium after every election dating back to 2012.

I have spoken on these subjects before audiences from across the political spectrum, including at the Heritage Foundation, the American Enterprise Institute, the CATO Institute, the Bipartisan Policy Center, and the Brookings Institution. In 2012, I was invited to Brussels to speak about American elections to the European External Action Service, which is the European Union's diplomatic corps. I was selected by the United States Embassy in Sweden to discuss the 2016 elections to a series of audiences there and was selected by the United States Embassy in Spain to fulfill a similar mission in 2018. I was invited to present by the United States Embassy in Italy, but was unable to do so because of my teaching schedule.

Education:

I am currently enrolled as a doctoral candidate in political science at The Ohio State University. I have completed all my coursework and have passed comprehensive examinations in both methods and American Politics. In pursuit of this degree, I have also earned a Master's Degree in Applied Statistics. My coursework for my Ph.D. and M.A.S. included, among other things, classes on G.I.S. systems, spatial statistics, issues in contemporary redistricting, machine learning, non-parametric hypothesis tests and probability theory.

In the winter of 2018, I taught American Politics and the Mass Media at Ohio Wesleyan University. I taught Introduction to American Politics at The Ohio State University for three semesters from Fall of 2018 to Fall of 2019, and again in Fall of 2021. In the Springs of 2020 and 2021, I taught Political Participation and Voting Behavior at The Ohio State University. This course spent several weeks covering all facets of redistricting: How maps are drawn, debates over what constitutes a fair map, measures of redistricting quality, and similar topics. I am teaching this course this semester as well.

Prior Engagements as an Expert:

In 2021, I served as one of two special masters appointed by the Supreme Court of Virginia to redraw the districts that will elect the Commonwealth's representatives to the House of Delegates, state Senate, and U.S. Congress in the following decade. The Supreme Court of Virginia

accepted those maps, which were praised by observers from across the political spectrum. "New Voting Maps, and a New Day, for Virginia," *The Washington Post* (Jan. 2, 2022), *available at* https://www.washingtonpost.com/opinions/2022/01/02/virginia-redistricting-voting-mapsgerrymandee; Henry Olsen, "Maryland Shows How to do Redistricting Wrong. Virginia Shows How to Do it Right," The Washington Post (Dec. 9, 2021), *available at* https://www. washingtonpost.com/opinions/2021/12/09/maryland-virginia-redistricting/; Richard Pildes, "Has VA Created a New Model for a Reasonably Non-Partisan Redistricting Process," *Election Law Blog* (Dec. 9, 2021), available at https://electionlawblog.org/?p=126216.

In 2019, I was appointed as the court's expert by the Supreme Court of Belize. In that case I was asked to identify international standards of democracy as they relate to malapportionment claims, to determine whether Belize's electoral divisions (similar to our congressional districts) conformed with those standards, and to draw alternative maps that would remedy any existing malapportionment.

I served as a Voting Rights Act expert to counsel for the Arizona Independent Redistricting Commission in 2021 and 2022.

I previously authored an expert report in *Dickson v. Rucho*, No. 11-CVS-16896 (N.C. Super Ct., Wake County), which involved North Carolina's 2012 General Assembly and Senate maps. Although I was not called to testify, it is my understanding that my expert report was accepted without objection.

I also authored an expert report in *Covington v. North Carolina*, Case 5 No. 1: 15-CV-00399 (M.D.N.C.), which involved almost identical challenges in a different forum. Due to what I understand to be a procedural quirk, where my largely identical report from Dickson had been inadvertently accepted by the plaintiffs into the record when they incorporated parts of the Dickson record into the case, I was not called to testify.

I authored two expert reports in *NAACP v. McCrory*, No. 1:13CV658 (M.D.N.C.), which involved challenges to multiple changes to North Carolina's voter laws. I was admitted as an expert witness and testified at trial. My testimony discussed the "effect" prong of the Voting Rights Act claim. I did not examine the issues relating to intent.

I authored reports in *NAACP v. Husted*, No. 2:14-cv-404 (S.D. Ohio), and *Ohio Democratic Party v. Mated*, Case 15-cv-01802 (S.D. Ohio), which dealt with challenges to various Ohio voting laws. I was admitted and testified at trial in the latter case (the former case settled). The judge in

the latter case ultimately refused to consider one opinion, where I used an internet map-drawing tool to show precinct locations in the state. Though no challenge to the accuracy of the data was raised, the judge believed I should have done more work to check that the data behind the application was accurate.

I served as a consulting expert in *Lee v. Virginia Board of Elections*, No. 3:15-cv-357 (E.D. Va. 2016), a voter identification case. Although I would not normally disclose consulting expert work, I was asked by defense counsel to sit in the courtroom during the case and review testimony. I would therefore consider my work de facto disclosed.

I filed an expert report in *Mecinas v. Hobbs*, No. CV-19-05547-PHX-DJH (D. Ariz. 2020). That case involved a challenge to Arizona's ballot order statute. Although the judge ultimately did not rule on a motion *in limine* in rendering her decision, I was allowed to testify at the hearing.

I authored two expert reports in *Feldman v. Arizona*, No. CV-16-1065-PHX-DLR (D. Ariz.). Plaintiffs in that case challenged an Arizona law prohibiting the collection of voted ballots by third parties that were not family members or caregivers and the practice of most of the state's counties to require voters to vote in their assigned precinct. My reports and testimony were admitted. Part of my trial testimony was struck in that case for reasons unrelated to the merits of the opinion; counsel for the state elicited it while I was on the witness stand and it was struck after Plaintiffs were not able to provide a rebuttal to the new evidence.

I authored an expert report in *Pascua Yaqui Tribe v. Rodriguez*, No. 4:20-CV-00432-TUC-JAS (D. Ariz.), which involved early voting. My expert report and testimony were admitted at trial.

I authored expert reports in *A. Philip Randolph Institute v. Smith*, No. 1 :18-cv-00357-TSB (S.D. Ohio), *Whitford v. Nichol*, No. 15-cv-421-bbc (W.D. Wisc.), and *Common Cause v. Rucho*, NO. 1:16-CV-1026-WO-JEP (M.D.N.C.), which were efficiency gap-based redistricting cases filed in Ohio, Wisconsin, and North Carolina.

I have only been excluded as an expert once, in *Fair Fight v. Raffensperger*. The judge concluded that I lacked sufficient credentials to testify as an expert in election administration.

I authored an expert report in the cases of *Ohio Organizing Collaborative, et al v. Ohio Redistricting Commission*, et al (No. 2021-1210); *League of Women Voters of Ohio, et al v. Ohio Redistricting Commission*, et al (No. 2021-1192); *Bria Bennett, et al v. Ohio Redistricting Commission*, et al (No. 2021-1 198). That case was decided on the written record.

I authored two expert reports in the consolidated cases of *NCLCV v. Hall* and *Harper v. Hall* (21 CVS 15426; 21 CVS 500085), two political/racial gerrymandering cases. My reports and testimony were admitted.

I authored two expert reports in the consolidated cases of *Montana Democratic Party v. Jacobson*, DV-56-2021-451 (Mont. Dist. Ct.). These cases involve the elimination of same-day registration, use of student identification to vote, and the restriction of ballot collection.

I authored an expert report on behalf of amicus curiae in the consolidated cases of *Carter v. Chapman* (No. 464 M.D. 2021) and *Gressman v. Chapman* (No. 465 M.D. 2021), which were redistricting cases before the Supreme Court of Pennsylvania.

I filed an expert report in *Harkenrider v. Hochul*, (No. E2022-0116CV), which is a partisan gerrymandering challenge to New York's enacted Congressional and state Senate maps. My reports and testimony were admitted.

I filed an expert report in *Szeliga v. Lamone*, Case No. C-02-CV-21-001816 (Md. Cir. Ct.) and *In the Matter of 2022 Legislative Redistricting of the State*, Misc. No. 25 (Md. Ct. App.), political gerrymandering cases in Maryland. My reports and testimony were admitted.

I filed an expert report in *Graham v. Adams*, (No. 22-CI-00047) (Ky. Cir. Ct.), a political gerrymandering case. I was admitted as an expert and allowed to testify as trial.

I filed an expert report in *NAACP v. McMaster*, (No. 3:21-cv-03302-JMC-T,11-1- RMG), which is a racial gerrymandering challenge to South Carolina's enacted state House maps.

II. Scope of Engagement

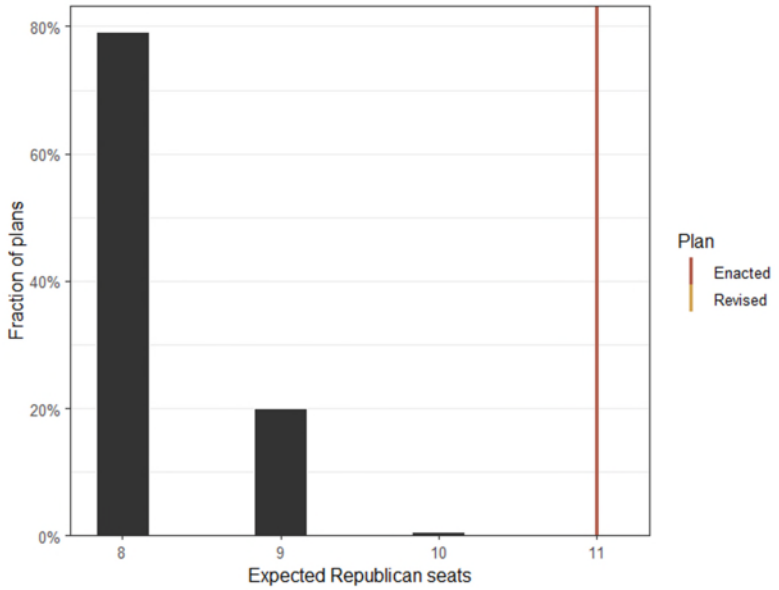
I have been retained by I have been retained by Nelson Mullins Riley & Scarborough, LLP on behalf of their clients, Speaker Cupp and Senate President Hoffman, to review the documents produced by Dr. Kosuke Imai on December 10, 2021 and March 6, 2022 relating to this case, in light of the most recent congressional plan passed on March ("Enacted Plan"). I have been retained and am being compensated at a rate of $400.00 per hour to provide my expert analysis of his statistical output.

III. Analysis

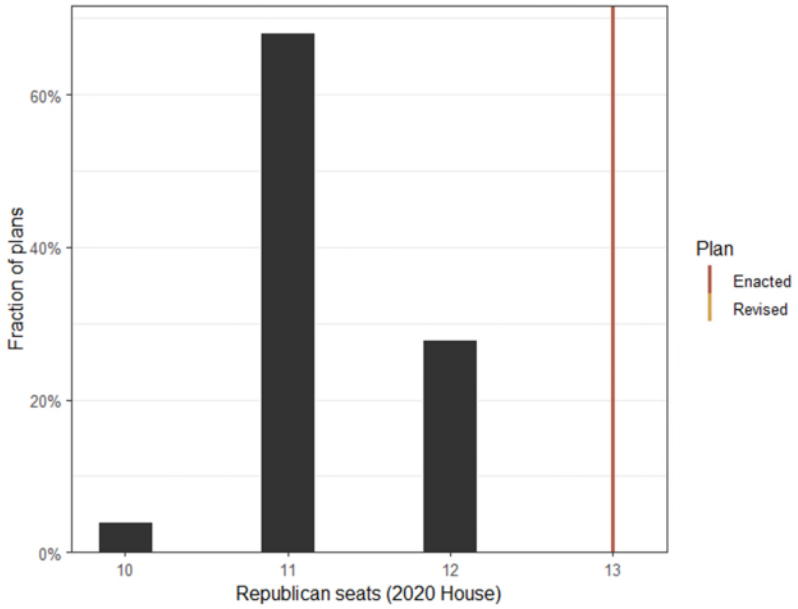
Using R, a widely used statistical programming language and data provided by Petitioners, I was able to reproduce the findings of Dr. Imai. Dr. Imai's code produces three sets of estimates for the partisanship of his ensembles. One, "ndv_fed," looks at the Democratic vote share in the federal races only dating back to 2012. Another, "ndv" looks at the Democratic vote share in

districts in 13 statewide races dating back to 2012. A third, "dem_house_2020," looks at the Republican congressional vote share in these districts.

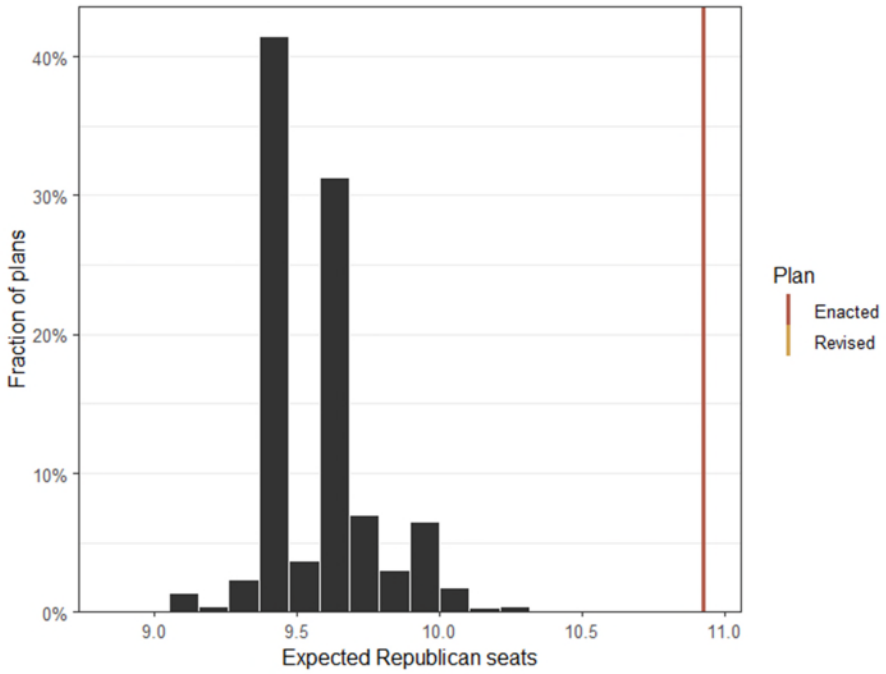
Dr. Imai's code produces the following histogram of maps from his ensemble using the "ndv_fed" metric – that is federal elections dating back to 2012 – with the partisanship of the initial plan superimposed. This is the histogram he included in his 2021 report.



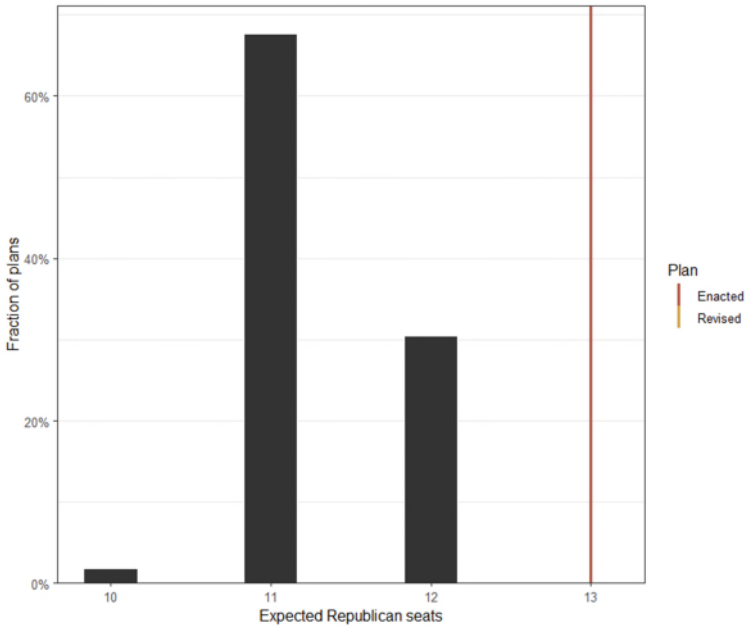
Dr. Imai also calculated the partisanship of the districts utilizing congressional race results. The histogram is as follows:



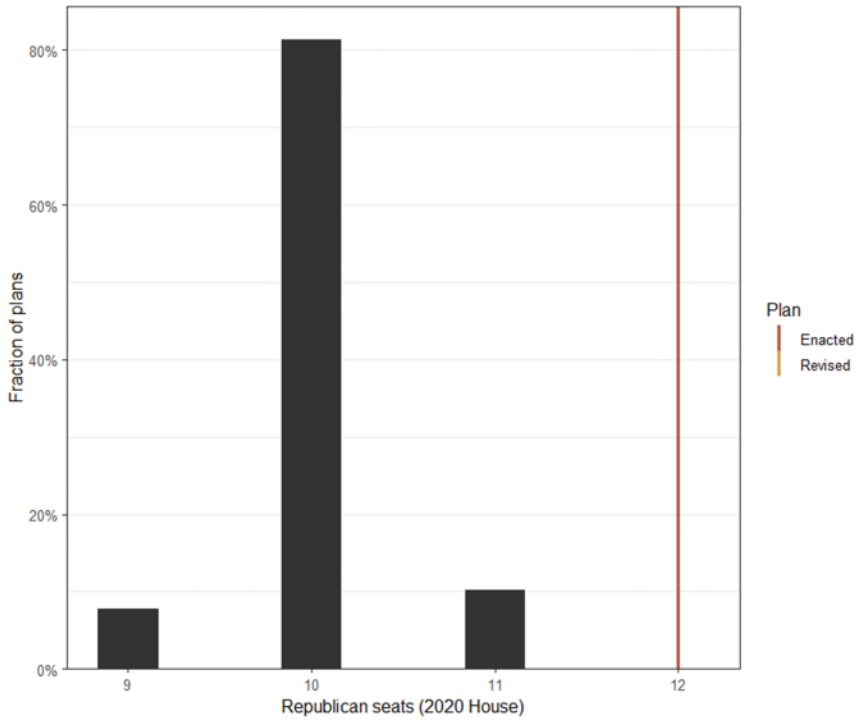
Finally, using the 13 statewide races dating back to 2012, Dr. Imai's code produces the following histogram:



You can also put this histogram of 13 statewide races on the same scale as the previous two histograms by changing a variable name in Dr. Imai's code:



In addition, Dr. Imai's simulations calculate the ensemble maps' partisanship using the state and federal elections from 2016-2020. This histogram is not programmed into his code, but I have created it below by changing a variable name in his code to access this data:



I have also calculated the Democratic vote share for the March 2, 2022 map using the different metrics described above. The results are as follows:

District	13 Races	2016-2020 Races	2012-2020 Federal Races	Congressional Elections
1	48.10%	51.01%	50.70%	50.10%
2	30.92%	30.26%	32.77%	24.74%
3	64.60%	68.87%	68.12%	68.90%
4	30.90%	32.13%	33.61%	29.30%
5	37.75%	38.66%	40.82%	34.13%
6	41.59%	40.93%	44.00%	34.42%
7	42.75%	45.59%	45.98%	40.55%
8	35.70%	37.39%	37.73%	37.19%
9	49.08%	50.25%	52.76%	46.85%
10	44.79%	46.68%	47.80%	42.60%
11	77.09%	79.85%	80.17%	78.26%
12	35.87%	36.70%	38.30%	30.61%
13	49.83%	52.17%	53.06%	48.72%
14	43.99%	45.17%	47.04%	39.95%
15	42.70%	45.79%	46.06%	42.97%

Finally, with respect to Dr. Imai's boxplots (see page 12), an observer may notice that there is a wide variety in the width of the bins of the boxes (these bins contain the partisanship level for half of the plans at each indexed value). For example, the 14th most Republican district has a wide box, ranging from 35%-45%, accompanied by whiskers that span from around 28% to 45%. On the other hand, the 8th most Republican district shows a line with no box, and no whiskers.

This can indicate a lack of variability in the way that districts are drawn. In other words, the algorithm may be so constrained that it simply will not select alternative arrangements of precincts. So, for example, the 14th most Republican district in Dr. Imai's algorithm consists of districts with 1,359 unique values of partisanship, using the federal race partisanship metric that Dr. Imai utilizes. Since these values of partisanship are decimals rounded to the nearest 10,000,000th, it would be an extreme coincidence if a district with a different configuration resulted

in the same partisanship estimate. In short, there are almost certainly 1,359 unique districts that fall into this bin, not 5,000.

The 15th-most Republican district, however, has almost no variation. Dr. Imai's maps produce only 13 unique variations on this district. The 13th-most Republican district has a bit more variation with 511 variations. The same is true of the 12th, with 215 variations.

Once we get into competitive territory, however, the number of variations plummet. It produces only 167 unique districts for the 11th-most Republican district, 142 for the 10th-most Republican district, 325 for the 9th-most Republican district, and just 47 unique drawings of the 8th-most Republican district.

One consequence of this is that if a map-drawer does not draw the 15th-most Republican district such that it falls between 21.3% Republican and 21.34% Republican, it will appear outside the "box" on the accompanying boxplot. Likewise, if one does not draw the 10th-most Republican district such that it falls between 48.7% and 49.25% Republican performance, it will fall outside the "box" on the accompanying boxplot. If one does not draw the 9th-most Republican district such that it falls between 49.7% and 49.83% Republican performance, it will fall outside the "box" on the accompanying boxplot. If one does not draw the 8th-most Republican district such that it falls ***exactly at*** 52.98% Republican performance, it will fall outside the "box" of the accompanying boxplot. The 7th-most Republican district must be between 53.06% and 53.16% Republican, or it will appear outside of the box in Dr. Imai's ensemble.

/s Sean Trende

4/25/2022