Supreme Court of Ohio Clerk of Court - Filed December 10, 2021 - Case No. 2021-1428

IN THE SUPREME COURT OF OHIO

Regina C. Adams, *et al.*, ***Relators,*** ***v.*** **Governor Mike DeWine, *et al.*,** ***Respondents.***	**Case No. 2021-1428** **Original Action Filed Pursuant to Ohio Const., Art. XIX, Sec. 3(A)**

EVIDENCE OF ADAMS RELATORS

(Affidavit of Raisa Cramer & Exhibits)

Abha Khanna (PHV 2189-2021)
Ben Stafford (PHV 25433-2021)
ELIAS LAW GROUP, LLP
1700 Seventh Ave., Suite 2100
Seattle, WA 98101
(206) 656-0176
akhanna@elias.law

Aria C. Branch (PHV 25435-2021)
Jyoti Jasrasaria (PHV 25401-2021)
Spencer W. Klein (PHV 25432-2021)
Harleen K. Gambhir (PHV 25587-2021)
ELIAS LAW GROUP, LLP
10 G St. NE, Suite 600
Washington, DC 20002
(202) 968-4490
abranch@elias.law

Donald J. McTigue (0022849)
Counsel of Record
Derek S. Clinger (0092075)
MCTIGUE & COLOMBO, LLC
545 East Town Street
Columbus, OH 43215
(614) 263-7000
dmctigue@electionlawgroup.com

Counsel for Adams Relators

Dave Yost
OHIO ATTORNEY GENERAL

Bridget C. Coontz (0072919)
Julie M. Pfeiffer (0069762)
Michael A. Walton (0092201)
Assistant Attorneys General
Constitutional Offices Section
30 E. Broad Street, 16th Floor
Columbus, OH 43215
(614) 466-2872
bridget.coontz@ohioago.gov

Counsel for Respondent Ohio Secretary of State Frank LaRose

Phillip J. Strach (PHV 25444-2021)
Thomas A. Farr (PHV 25461-2021)
John E. Branch, III (PHV 25460-2021)
Alyssa M. Riggins (PHV 25441-2021)
NELSON MULLINS RILEY & SCARBOROUGH, LLP
4140 Parklake Ave., Suite 200
Raleigh, NC 27612
(919) 329-3812
phil.strach@nelsonmullins.com

Counsel for Respondents House Speaker Bob Cupp and Senate President Matt Huffman

Affidavit of Raisa Cramer

I, Raisa Cramer, having been duly sworn and cautioned according to law, hereby state that I am over the age of eighteen years and am competent to testify as to the facts set forth below based on my personal knowledge and having personally examined all records referenced in this affidavit, and further state as follows:

1. In the above-captioned case, the Ohio Supreme Court has entered an order providing that parties shall file any evidence they intend to present no later than Friday, December 8, 2021 at 4:00 p.m.
2. I am a law clerk at Elias Law Group LLP, which serves as legal counsel to the Relators in this action.
3. Document 1 is a true and correct copy of the affidavit of Relator Regina C. Adams dated December 7, 2021.
4. Document 2 is a true and correct copy of the affidavit of Relator Bria Bennett dated December 9, 2021.
5. Document 3 is a true and correct copy of the affidavit of Relator Kathleen M. Brinkman dated December 8, 2021.
6. Document 4 is a true and correct copy of the affidavit of Relator Martha Clark dated December 7, 2021.
7. Document 5 is a true and correct copy of the affidavit of Relator Susanne L. Dyke dated December 8, 2021.
8. Document 6 is a true and correct copy of the affidavit of Relator Carrie Kubicki dated December 7, 2021.

9. Document 7 is a true and correct copy of the affidavit of Relator Dana Miller dated December 6, 2021.

10. Document 8 is a true and correct copy of the affidavit of Relator Meryl Neiman dated December 6, 2021.

11. Document 9 is a true and correct copy of the affidavit of Relator Holly Oyster dated December 9, 2021.

12. Document 10 is a true and correct copy of the affidavit of Relator Constance Rubin dated December 8, 2021.

13. Document 11 is a true and correct copy of the affidavit of Relator Solveig Spjeldnes dated December 7, 2021.

14. Document 12 is a true and correct copy of the affidavit of Relator Everett Totty dated December 6, 2021.

15. Document 13 is a true and correct copy of the expert affidavit of Dr. Christopher Warshaw, as filed in *League of Women Voters, et al. v. Ohio Redistricting Commission, et al.*, Ohio Supreme Court Case No. 2021-1449, on November 30, 2021.

16. Document 14 is a true and correct copy of the expert affidavit of Dr. Kosuke Imai, as filed in *League of Women Voters, et al. v. Ohio Redistricting Commission, et al.*, Ohio Supreme Court Case No. 2021-1449, on December 9, 2021.

17. Document 15 is a true and correct copy of the expert affidavit of Dr. Lisa Handley, as filed in *League of Women Voters, et al. v. Ohio Redistricting Commission, et al.*, Ohio Supreme Court Case No. 2021-1449, on December 9, 2021.

18. Document 16 is a true and correct copy of the affidavit of Congresswoman Marcy Kaptur, as filed in *League of Women Voters, et al. v. Ohio Redistricting Commission, et al.*, Ohio Supreme Court Case No. 2021-1449, on December 9, 2021.

19. The Index at the beginning of the Appendix gives a description of each document and states where it appears in the Appendix.

Raisa Marie Cramer

Raisa Cramer

JURAT

STATE OF FLORIDA
COUNTY OF SAINT LUCIE

Sworn to before me this 10th day of December 2021.

By Raisa Marie Cramer

Form of ID Produced: Driver's License

Darrell Dwayne Evans

Notary Public Darrell Dwayne Evans

NOTARY PUBLIC STATE OF FLORIDA
DARRELL DWAYNE EVANS
Notary Public - State of Florida
Commission # HH 81836
Expires on January 19, 2025

My commission expires 01/19/2025

Notarized online using audio-video communication

CERTIFICATE OF SERVICE

I hereby certify that the foregoing was sent via email this 10th day of December, 2021 to the following:

Bridget C. Coontz, bridget.coontz@ohioago.gov
Julie M. Pfeiffer, julie.pfeiffer@ohioago.gov
Michael Walton, michael.walton@ohioago.gov

Counsel for Respondents Ohio Governor DeWine, Ohio Secretary of State LaRose, Ohio Auditor Faber, House Speaker Robert R. Cupp, Senate President Matt Huffman, Senator Vernon Sykes, House Minority Leader Emilia Sykes, and Ohio Redistricting Commission

W. Stuart Dornette, dornette@taftlaw.com
Beth A. Bryan, bryan@taftlaw.com
Philip D. Williamson, pwilliamson@taftlaw.com
Phillip J. Strach, phil.strach@nelsonmullins.com
Thomas A. Farr, tom.farr@nelsonmullins.com
John E. Branch, III, john.branch@nelsonmullins.com
Alyssa M. Riggins, alyssa.riggins@nelsonmullins.com

Counsel for Respondents House Speaker Robert R. Cupp and Senate President Matt Huffman

/s/ Derek S. Clinger_________
Derek S. Clinger (0092075)

How to Verify This Transaction

Every Notarize transaction is recorded and saved for a minimum of five years. Whether you receive an electronic or printed paper copy of a Notarize document, you can access details of the transaction and verify its authenticity with the information below.

To get started, visit verify.notarize.com and enter this information:

Notarize ID:	PRQZKCVP
Access PIN:	WWWUW6

For more information on how to verify Notarize transactions, please visit:
support.notarize.com/notarize-for-signers/verifying-document-authenticity

Notarize

AFFIDAVIT OF RAISA CRAMER – APPENDIX OF EXHIBITS

Index of Documents

ITEM	DESCRIPTION	BATES RANGE
1	Affidavit of Relator Regina C. Adams dated December 8, 2021	ADAMS_00001-02
2	Affidavit of Relator Bria Bennett dated December 9, 2021	ADAMS_00003
3	Affidavit of Relator Kathleen M. Brinkman dated December 8, 2021	ADAMS_00004
4	Affidavit of Relator Martha Clark dated December 7, 2021	ADAMS_00005
5	Affidavit of Relator Susanne L. Dyke dated December 8, 2021	ADAMS_00006-07
6	Affidavit of Relator Carrie Kubicki dated December 7, 2021	ADAMS_00008
7	Affidavit of Relator Dana Miller dated December 6, 2021	ADAMS_00009-10
8	Affidavit of Relator Meryl Neiman dated December 6, 2021	ADAMS_00011-12
9	Affidavit of Relator Holly Oyster dated December 9, 2021	ADAMS_00013
10	Affidavit of Relator Constance Rubin dated December 8, 2021	ADAMS_00014-16
11	Affidavit of Relator Solveig Spjeldnes dated December 7, 2021	ADAMS_00017
12	Affidavit of Relator Everett Totty dated December 6, 2021	ADAMS_00018
13	Affidavit of Dr. Christopher Warshaw submitted November 30, 2021	ADAMS_00019-54
14	Affidavit of Congresswomen Marcy Kaptur served December 9, 2021	ADAMS_00055-112
15	Affidavit of Dr. Lisa Handley served December 9, 2021	ADAMS_00113-37
16	Affidavit of Professor Kosuke Imai served December 9, 2021	ADAMS_00138-40

IN THE SUPREME COURT OF OHIO

Regina C. Adams, *et al.*, **Relators,** **v.** **Governor Mike DeWine, *et al.*,** **Respondents.**	**Case No. 2021-1428** Original Action Filed Pursuant to Ohio Constitution, Article XIX, Section 3(A)

AFFIDAVIT OF REGINA C. ADAMS

I, Regina C. Adams, having been duly sworn and cautioned according to law, hereby state that I am over the age of eighteen years and am competent to testify to the facts set forth below based on my personal knowledge, and further state as follows:

1. I am a citizen of the United States and a qualified elector in the State of Ohio.

2. I am registered to vote and regularly request a Democratic ballot in partisan primary elections. I have consistently voted for Democratic candidates for U.S. Congress.

3. I reside at 14360 Rockside Rd., Maple Heights, OH 44137, which is in District 11 in the 2021 Congressional Plan.

4. My address is in District 11 in the current Plan that was adopted in 2011.

Regina C Adams

Regina C. Adams

Sworn to before me this 7th day of December, 2021.by Regina Claudine Adams.

Abbie L

Notary Public

NOTARY PUBLIC STATE OF TEXAS

Abbie Lee

ID NUMBER 132713205

COMMISSION EXPIRES October 6, 2024

My commission expires 10/06/2024

Notarized online using audio-video communication

How to Verify This Transaction

Every Notarize transaction is recorded and saved for a minimum of five years. Whether you receive an electronic or printed paper copy of a Notarize document, you can access details of the transaction and verify its authenticity with the information below.

To get started, visit verify.notarize.com and enter this information:

Notarize ID:	4NKS4QR3
Access PIN:	D7U9K2

For more information on how to verify Notarize transactions, please visit:
support.notarize.com/notarize-for-signers/verifying-document-authenticity

Notarize

IN THE SUPREME COURT OF OHIO

Regina C. Adams *et al.*,	
Relators,	**Case No. 2021-1428**
v.	Original Action Filed Pursuant to Ohio Constitution, Article XIX, Section 3(A)
Governor Mike DeWine, *et al.*,	
Respondents.	

AFFIDAVIT OF BRIA BENNETT

I, Bria Bennett, having been duly sworn and cautioned according to law, hereby state that I am over the age of eighteen years and am competent to testify to the facts set forth below based on my personal knowledge, and further state as follows:

1. I am a citizen of the United States and a qualified elector in the State of Ohio.

2. I am registered to vote and regularly request a Democratic ballot in partisan primary elections. I have consistently voted for Democratic candidates for U.S. Congress.

3. I reside at 2977 Dunstan Dr. NW, Warren, OH 44485, which is in District 6 in the 2021 Congressional Plan.

4. My address is in District 13 in the current Plan that was adopted in 2011.

Bria L Bennett

Bria Bennett

Sworn to before me this 9th day of December, 2021.

Pamela J. Neiswanger

Notary Public

NOTARY PUBLIC ★ STATE OF OHIO ★

PAMELA J. NEISWANGER, Notary Public
STATE OF OHIO
My Commission Expires January 2, 2022

My commission expires ______________

IN THE SUPREME COURT OF OHIO

Regina C. Adams, *et al.*, **Relators,** **v.** **Governor Mike DeWine, *et al.*,** **Respondents.**	**Case No. 2021-1428** Original Action Filed Pursuant to Ohio Constitution, Article XIX, Section 3(A)

AFFIDAVIT OF KATHLEEN M. BRINKMAN

I, Kathleen M. Brinkman, having been duly sworn and cautioned according to law, hereby state that I am over the age of eighteen years and am competent to testify to the facts set forth below based on my personal knowledge, and further state as follows:

1. I am a citizen of the United States and a qualified elector in the State of Ohio.

2. I am registered to vote and regularly request a Democratic ballot in partisan primary elections. I have consistently voted for Democratic candidates for U.S. Congress.

3. I reside at 400 Pike St. Unit 809, Cincinnati, OH 45202, which is in District 1 in the 2021 Congressional Plan.

4. My address is in District 1 in the current Plan that was adopted in 2011.

Kathleen M. Brinkman

Kathleen M. Brinkman

Sworn to before me this 8th day of December, 2021.

Paul M. DeMarco

Notary Public

NOTARIAL SEAL STATE OF OHIO

PAUL DE MARCO
Attorney at Law
Notary Public, State of Ohio
My Commission Has No Expiration
Section 147.03 R.C.

My commission expires Never

IN THE SUPREME COURT OF OHIO

Regina C. Adams *et al.*, **Relators,** v. **Governor Mike DeWine, *et al.*,** **Respondents.**	**Case No. 2021-1428** Original Action Filed Pursuant to Ohio Constitution, Article XIX, Section 3(A)

AFFIDAVIT OF MARTHA CLARK

I, Martha Clark, having been duly sworn and cautioned according to law, hereby state that I am over the age of eighteen years and am competent to testify to the facts set forth below based on my personal knowledge, and further state as follows:

1. I am a citizen of the United States and a qualified elector in the State of Ohio.
2. I am registered to vote and regularly request a Democratic ballot in partisan primary elections. I have consistently voted for Democratic candidates for U.S. Congress.
3. I reside at 4439 Filbrun Ln., Trotwood, OH 45426, which is in District 10 in the 2021 Congressional Plan.
4. My address is in District 10 in the current Plan that was adopted in 2011.

Martha Clark
Martha Clark

Sworn to before me this 7th day of December, 2021.

Notary Public

NOTARY PUBLIC STATE OF OHIO

JACOB MUNN
Notary Public
State of Ohio
My Comm. Expires
November 14, 2024

My commission expires 11-14-2024

IN THE SUPREME COURT OF OHIO

Regina C. Adams *et al.*, **Relators,** **v.** **Governor Mike DeWine, *et al.*,** **Respondents.**	**Case No. 2021-1428** Original Action Filed Pursuant to Ohio Constitution, Article XIX, Section 3(A)

AFFIDAVIT OF SUSANNE L DYKE

I, Susanne L. Dyke, having been duly sworn and cautioned according to law, hereby state that I am over the age of eighteen years and am competent to testify to the facts set forth below based on my personal knowledge, and further state as follows:

1. I am a citizen of the United States and a qualified elector in the State of Ohio.

2. I am registered to vote and regularly request a Democratic ballot in partisan primary elections. I have consistently voted for Democratic candidates for U.S. Congress.

3. I reside at 2558 Guilford Rd., Cleveland Heights, OH 44118, which is in District 11 in the 2021 Congressional Plan.

4. My address is in District 11 in the current Plan that was adopted in 2011.

Susanne Luisa Dyke

Susanne L. Dyke

State of Florida, County of Orange

Sworn to before me this 8th day of December, 2021.

By Susanne L Dyke Type of ID Produced: Driver License

Karl Berry Joseph

Notary Public Karl Berry Joseph

NOTARY PUBLIC • STATE OF FLORIDA •
KARL BERRY JOSEPH
Notary Public - State of Florida
Commission # HH 72342
Expires on December 15, 2024

My commission expires 12/15/2024

Notarized online using audio-video communication

How to Verify This Transaction

Every Notarize transaction is recorded and saved for a minimum of five years. Whether you receive an electronic or printed paper copy of a Notarize document, you can access details of the transaction and verify its authenticity with the information below.

To get started, visit verify.notarize.com and enter this information:

Notarize ID:	Z7TY4BNH
Access PIN:	92EN46

For more information on how to verify Notarize transactions, please visit:
support.notarize.com/notarize-for-signers/verifying-document-authenticity

Notarize

IN THE SUPREME COURT OF OHIO

Regina C. Adams *et al.*, **Relators,** v. **Governor Mike DeWine, *et al.*,** **Respondents.**	**Case No. 2021-1428** Original Action Filed Pursuant to Ohio Constitution, Article XIX, Section 3(A)

AFFIDAVIT OF CARRIE KUBICKI

I, Carrie Kubicki, having been duly sworn and cautioned according to law, hereby state that I am over the age of eighteen years and am competent to testify to the facts set forth below based on my personal knowledge, and further state as follows:

1. I am a citizen of the United States and a qualified elector in the State of Ohio.

2. I am registered to vote and regularly request a Democratic ballot in partisan primary elections. I have consistently voted for Democratic candidates for U.S. Congress.

3. I reside at 13201 Vermillion Rd., Amherst, OH 44001, which is in District 5 in the 2021 Congressional Plan.

4. My address is in District 4 in the current Plan that was adopted in 2011.

Carrie Kubicki

Sworn to before me this 7 day of December, 2021.

Notary Public

My commission expires 18 April 2022

IN THE SUPREME COURT OF OHIO

Regina C. Adams *et al.*, **Relators,** **v.** **Governor Mike DeWine, *et al.*,** **Respondents.**	**Case No. 2021-1428** Original Action Filed Pursuant to Ohio Constitution, Article XIX, Section 3(A)

AFFIDAVIT OF DANA MILLER

I, Dana Miller, having been duly sworn and cautioned according to law, hereby state that I am over the age of eighteen years and am competent to testify to the facts set forth below based on my personal knowledge, and further state as follows:

1. I am a citizen of the United States and a qualified elector in the State of Ohio.

2. I am registered to vote and regularly request a Democratic ballot in partisan primary elections. I have consistently voted for Democratic candidates for U.S. Congress.

3. I reside at 1211 Dana Dr., Oxford, OH 45056, which is in District 8 in the 2021 Congressional Plan.

4. My address is in District 8 in the current Plan that was adopted in 2011.

Dana P MillerD

Dana Miller

Commonwealth of Virginia

County of Chesapeake

Sworn to before me this 6th day of December, 2021.

Brenda Turner

Brenda Turner

Notary Public

Electronic Notary Public

COMMONWEALTH OF VIRGINIA • ELECTRONIC NOTARY PUBLIC • N

Brenda Turner

REGISTRATION NUMBER
7920382
COMMISSION EXPIRES
October 31, 2025

My commission expires 10/31/2025

Notarized online using audio-video communication

How to Verify This Transaction

Every Notarize transaction is recorded and saved for a minimum of five years. Whether you receive an electronic or printed paper copy of a Notarize document, you can access details of the transaction and verify its authenticity with the information below.

To get started, visit verify.notarize.com and enter this information:

Notarize ID:	VTJSEHFV
Access PIN:	Y983WF

For more information on how to verify Notarize transactions, please visit:
support.notarize.com/notarize-for-signers/verifying-document-authenticity

Notarize

IN THE SUPREME COURT OF OHIO

Regina C. Adams, *et al.*, **Relators,** **v.** **Governor Mike DeWine, *et al.*,** **Respondents.**	**Case No. 2021-1428** Original Action Filed Pursuant to Ohio Constitution, Article XIX, Section 3(A)

AFFIDAVIT OF MERYL NEIMAN

I, Meryl Neiman, having been duly sworn and cautioned according to law, hereby state that I am over the age of eighteen years and am competent to testify to the facts set forth below based on my personal knowledge, and further state as follows:

1. I am a citizen of the United States and a qualified elector in the State of Ohio.

2. I am registered to vote and regularly request a Democratic ballot in partisan primary elections. I have consistently voted for Democratic candidates for U.S. Congress.

3. I reside at 2115 Clifton Ave. Columbus, OH 43209, which is in District 3 in the 2021 Congressional Plan.

4. My address is in District 3 in the current Plan that was adopted in 2011.

Meryl Jean Neiman

Meryl Neiman

Sworn to and subscribed before me on

RS ~~Sworn to before me this~~ 6th day of December, 2021, by Meryl Jean Neiman.

Roncielle Stokes

Notary Public, State of Texas

Notary Public

State of Texas County of Tarrant

NOTARY PUBLIC STATE OF TEXAS

Roncielle Stokes

ID NUMBER
13261614-1
COMMISSION EXPIRES
August 11, 2024

My commission expires 08/11/2024

Notarized online using audio-video communication

How to Verify This Transaction

Every Notarize transaction is recorded and saved for a minimum of five years. Whether you receive an electronic or printed paper copy of a Notarize document, you can access details of the transaction and verify its authenticity with the information below.

To get started, visit verify.notarize.com and enter this information:

Notarize ID:	X623GFMM
Access PIN:	CD9F94

For more information on how to verify Notarize transactions, please visit:
support.notarize.com/notarize-for-signers/verifying-document-authenticity

Notarize

IN THE SUPREME COURT OF OHIO

Regina C. Adams *et al.*, **Relators,** **v.** **Governor Mike DeWine, *et al.*,** **Respondents.**	**Case No. 2021-1428** Original Action Filed Pursuant to Ohio Constitution, Article XIX, Section 3(A)

AFFIDAVIT OF HOLLY OYSTER

I, Holly Oyster, having been duly sworn and cautioned according to law, hereby state that I am over the age of eighteen years and am competent to testify to the facts set forth below based on my personal knowledge, and further state as follows:

1. I am a citizen of the United States and a qualified elector in the State of Ohio.

2. I am registered to vote and regularly request a Democratic ballot in partisan primary elections. I have consistently voted for Democratic candidates for U.S. Congress.

3. I reside at 21370 Harrisburg Westville Rd., Alliance, OH 44601, which is in District 6 in the 2021 Congressional Plan.

4. My address is in District 6 in the current Plan that was adopted in 2011.

Holly Oyster

Sworn to before me this 9 day of December, 2021.

Notary Public

NOTARIAL SEAL
STATE OF OHIO

STACEY SHANK
Notary Public, State of Ohio
My Commission Expires:
12/03/2024

My commission expires 12/3/24

IN THE SUPREME COURT OF OHIO

Regina C. Adams *et al.*, **Relators,** **v.** **Governor Mike DeWine, *et al.*,** **Respondents.**	**Case No. 2021-1428** Original Action Filed Pursuant to Ohio Constitution, Article XIX, Section 3(A)

AFFIDAVIT OF CONSTANCE RUBIN

I, Constance Rubin, having been duly sworn and cautioned according to law, hereby state that I am over the age of eighteen years and am competent to testify to the facts set forth below based on my personal knowledge, and further state as follows:

1. I am a citizen of the United States and a qualified elector in the State of Ohio.

2. I am registered to vote and regularly request a Democratic ballot in partisan primary elections. I have consistently voted for Democratic candidates for U.S. Congress.

3. I reside at 3088 Whitewood St. NW, North Canton, OH 44720, which is in District 7 in the 2021 Congressional Plan.

4. My address is in District 16 in the current Plan that was adopted in 2011.

Constance G Rubin
Constance Rubin

Sworn to before me this _______ day of December, 2021.

see attached certificate
Notary Public

My commission expires ________________________

JURAT

State/Commonwealth of VIRGINIA)

☐ City ☑ County of Chesapeake)

)

On 12/08/2021, before me, Kelly Sue Parker ,
Date *Notary Name*

the foregoing instrument was subscribed and sworn (or affirmed) before me by:

Constance G Rubin .
Name of Affiant(s)

☐ Personally known to me **-- OR --**

☐ Proved to me on the basis of the oath of ______________________ **-- OR --**
Name of Credible Witness

☑ Proved to me on the basis of satisfactory evidence: driver_license
Type of ID Presented

COMMONWEALTH OF VIRGINIA · ELECTRONIC NOTARY PUBLIC

N

Kelly Sue Parker

REGISTRATION NUMBER
7910155
COMMISSION EXPIRES
February 28, 2025

WITNESS my hand and official seal.

Notary Public Signature: Kelly Sue Parker

Notary Name: Kelly Sue Parker

Notary Commission Number: 7910155

Notary Commission Expires: 02/28/2025

Notarized online using audio-video communication

DESCRIPTION OF ATTACHED DOCUMENT

Title or Type of Document: Rubin Affidavit

Document Date: 12/08/2021

Number of Pages (including notarial certificate): 2

How to Verify This Transaction

Every Notarize transaction is recorded and saved for a minimum of five years. Whether you receive an electronic or printed paper copy of a Notarize document, you can access details of the transaction and verify its authenticity with the information below.

To get started, visit verify.notarize.com and enter this information:

Notarize ID:	VK6S7RBY
Access PIN:	EPAZX3

For more information on how to verify Notarize transactions, please visit:
support.notarize.com/notarize-for-signers/verifying-document-authenticity

Notarize

IN THE SUPREME COURT OF OHIO

Regina C. Adams ***et al.*****,** **Relators,** **v.** **Governor Mike DeWine,** ***et al.*****,** **Respondents.**	**Case No. 2021-1428** Original Action Filed Pursuant to Ohio Constitution, Article XIX, Section 3(A)

AFFIDAVIT OF SOLVEIG SPJELDNES

I, Solveig Spjeldnes, having been duly sworn and cautioned according to law, hereby state that I am over the age of eighteen years and am competent to testify to the facts set forth below based on my personal knowledge, and further state as follows:

1. I am a citizen of the United States and a qualified elector in the State of Ohio.

2. I am registered to vote and regularly request a Democratic ballot in partisan primary elections. I have consistently voted for Democratic candidates for U.S. Congress.

3. I reside at 87 University Estates Blvd., Athens, OH 45701, which is in District 12 in the 2021 Congressional Plan.

4. My address is in District 15 in the current Plan that was adopted in 2011.

Solveig Spjeldnes

Solveig Spjeldnes

Sworn to before me this 7 day of December, 2021.

Alexander Hoskins

Notary Public

NOTARIAL SEAL STATE OF OHIO

ALEXANDER HOSKINS
Notary Public, State of Ohio
My Commission Expires 07-01-23
Commission Recorded in Athens County

My commission expires 7/1/23

IN THE SUPREME COURT OF OHIO

Regina C. Adams *et al.*, **Relators,** **v.** **Governor Mike DeWine, *et al.*,** **Respondents.**	**Case No. 2021-1428** Original Action Filed Pursuant to Ohio Constitution, Article XIX, Section 3(A)

AFFIDAVIT OF EVERETT TOTTY

I, Everett Totty, having been duly sworn and cautioned according to law, hereby state that I am over the age of eighteen years and am competent to testify to the facts set forth below based on my personal knowledge, and further state as follows:

1. I am a citizen of the United States and a qualified elector in the State of Ohio.

2. I am registered to vote and regularly request a Democratic ballot in partisan primary elections. I have consistently voted for Democratic candidates for U.S. Congress.

3. I reside at 145 S. St. Clair St., Unit 28, Toledo, OH 43604, which is in District 9 in the 2021 Congressional Plan.

4. My address is in District 9 in the current Plan that was adopted in 2011.

Everett Totty

Everett Totty

Sworn to before me this 6 day of December, 2021.

Madeline Tucker

Notary Public

MADELINE TUCKER
Notary Public, State of Ohio
My Comm. Expires Dec. 14, 2025

NOTARY PUBLIC STATE OF OHIO

My commission expires 12-14-25

Warshaw Affidavit.pdf

DocVerify ID:	B2B166DB-6377-4273-B752-0BC7D6BF945B
Created:	November 30, 2021 08:02:22 -8:00
Pages:	1
Remote Notary:	Yes / State: OH

This document is a DocVerify VeriVaulted protected version of the document named above. It was created by a notary or on the behalf of a notary, and it is also a DocVerify E-Sign document, which means this document was created for the purposes of Electronic Signatures and/or Electronic Notary. Tampered or altered documents can be easily verified and validated with the DocVerify veriCheck system. This remote online notarization involved the use of communication technology.

Go to www.docverify.com at any time to verify or validate the authenticity and integrity of this or any other DocVerify VeriVaulted document.

E-Signature Summary

E-Signature 1: Christopher Warshaw (CW)
November 30, 2021 08:13:08 -8:00 [9105E3126672] [68.33.74.68]
warshaw@email.gwu.edu (Principal) (Personally Known)

E-Signature Notary: Theresa M Sabo (TMS)
November 30, 2021 08:13:08 -8:00 [0C271766C922] [74.142.214.254]
tess.sabo@gmail.com
I, Theresa M Sabo, did witness the participants named above electronically sign this document.

DocVerify documents cannot be altered or tampered with in any way once they are protected by the DocVerify VeriVault System. Best viewed with Adobe Reader or Adobe Acrobat. All visible electronic signatures contained in this document are symbolic representations of the persons signature, and not intended to be an accurate depiction of the persons actual signature as defined by various Acts and/or Laws.

IN THE SUPREME COURT OF OHIO

LEAGUE OF WOMEN VOTERS OF OHIO, et al.,	
Relators	**Case No.**
v.	**Original Action Pursuant to Ohio Const., Art. XIX**
GOVERNOR MIKE DEWINE, et al.,	
Respondents.	

AFFIDAVIT OF CHRISTOPHER WARSHAW

Franklin County
/ss
State of Ohio

Now comes affiant Christopher Warshaw, having been first duly cautioned and sworn, deposes and states as follows:

1. I am over the age of 18 and fully competent to make this declaration. I have personal knowledge of the statements and facts contained herein.
2. For the purposes of this litigation, I have been asked by counsel for Relators to analyze relevant data and provide my expert opinions.
3. To that end, I have personally prepared the report attached to this affidavit as Exhibit A, and swear to its authenticity and to the faithfulness of the opinions expressed and, to the best of my knowledge, the accuracy of the factual statements made therein.

FURTHER AFFIANT SAYETH NAUGHT.

Executed on 11/30/2021, 2021.

Christopher Warshaw
Signed on 2021/11/30 08:13:08 -8:00

Christopher Warshaw

Sworn and subscribed before me this ____ day of 11/30/2021, 2021.

Signed on 2021/11/30 08:13:08 -8:00

Notary Public

NOTARY PUBLIC
STATE OF OHIO

Theresa M Sabo
Commission # 2016-RE-619622
Electronic Notary Public
State of Ohio
My Comm Exp. Nov 28, 2026

Notary Stamp 2021/11/30 09:13:08 PST 0C271766C922

Notarial act performed by audio-visual communication

B2B166DB-6377-4273-B752-0BC7D6BF945B --- 2021/11/30 08:02:22 -8:00 --- Remote Notary

DocVerify ID: B2B166DB-6377-4273-B752-0BC7D6BF945B
www.docverify.com

Page 1 of 1 10BC7D6BF945B

EXHIBIT A

An Evaluation of the Partisan Bias in Ohio's Enacted Congressional Districting Plan

Christopher Warshaw*

November 30, 2021

*Associate Professor, Department of Political Science, George Washington University. warshaw@gwu.edu. Note that the analyses and views in this report are my own, and do not represent the views of George Washington University.

Contents

ADAMS_00023

1 Introduction

My name is Christopher Warshaw. I am an Associate Professor of Political Science at George Washington University. Previously, I was an Associate Professor at the Massachusetts Institute of Technology from July 2016 - July 2017, and an Assistant Professor at MIT from July 2012 - July 2016.

I have been asked by counsel representing the relators in this case to analyze relevant data and provide my expert opinions about whether Ohio's enacted congressional districting plan meets the requirement in Article XIX.01, Section 3(A) of Ohio's Constitution that "If the general assembly passes a congressional district plan under division (C)(1) of this section by a simple majority of the members of each house of the general assembly, and not by the vote described in division (C)(2) of this section", then "The general assembly shall not pass a plan that unduly favors or disfavors a political party or its incumbents."

2 Qualifications, Publications and Compensation

My Ph.D. is in Political Science, from Stanford University, where my graduate training included courses in political science and statistics. I also have a J.D. from Stanford Law School. My academic research focuses on public opinion, representation, elections, and polarization in American Politics. I have written over 20 peer reviewed papers on these topics. Moreover, I have written multiple papers that focus on elections and two articles that focus specifically on partisan gerrymandering. I also have a forthcoming book that includes an extensive analysis on the causes and consequences of partisan gerrymandering in state governments.

My curriculum vitae is attached to this report. All publications that I have authored and published appear in my curriculum vitae. My work is published or forthcoming in peer-reviewed journals such as: the *American Political Science Review*, the *American Journal of Political Science*, the *Journal of Politics*, *Political Analysis*, *Political Science Research and Methods*, the *British Journal of Political Science*, the *Annual Review of Political Science*, *Political Behavior*, *Legislative Studies Quarterly*, *Science Advances*, the *Election Law Journal*, *Nature Energy*, *Public Choice*, and edited volumes from Cambridge University Press and Oxford University Press. My book entitled *Dynamic Democracy in the American States* is forthcoming from the University of Chicago Press. My non-academic writing has been published in the *New York Times* and the *Washington Post*. My work has also been discussed in the *Economist* and many other prominent media outlets.

My opinions in this case are based on the knowledge I have amassed over my education, training and experience, including a detailed review of the relevant academic literature. They also follow from statistical analysis of the following data:

- In order to calculate partisan bias in congressional elections on the enacted plan in Ohio, I examined:
  - GIS Files with the 2012-2020 Ohio Congressional plan and the enacted 2022-24 plan): I obtained the 2012-2020 plan from the state website and the enacted plan from Counsel in this case.
  - Precinct-level data on recent statewide Ohio elections: I use precinct-level data on Ohio's statewide elections between 2016-20 from the Voting and Election Science Team (University of Florida, Wichita State University). I obtained these data from the Harvard Dataverse.[1] As far as I know, there are no publicly available datasets with precinct-level returns from 2012-14 that are linked to precinct boundaries (e.g., shapefiles). For these elections, I obtained data via the ACLU that Bill Cooper, the relators' expert in League of Women Voters v. Ohio Redistricting Commission, No. 2021-1193, put together.[2]
  - Precinct-level data on recent statewide Ohio elections: I use a GIS file with precinct-level data on the results of the 2020 congressional elections in Ohio that I obtained from Counsel in this case.
  - The Plan Score website: PlanScore is a project of the nonpartisan Campaign Legal Center (CLC) that enables people to score proposed maps for their partisan, demographic, racial, and geometric features. I am on the social science advisory team for PlanScore.

1. See `https://dataverse.harvard.edu/dataverse/electionscience`.

2. Cooper provided the following description of the data via Counsel: The 2012 results are disaggregated to the block level (based on block centroids) from the statewide 2012 precinct file. The 2014 results are based on a geocoding of about 3.15 million voters who cast ballots in Nov. 2014. These addresses were matched to census blocks and the blocks were aggregated to the precinct level. These "virtual" precincts were next matched to the 2014 election results and then disaggregated back to the block level, with block-level matches. When aggregated to the congressional level, the differences are measured in the tenths of a percent for House contests. As a final step, these datasets were aggregated from the block-level to the 2010 VTD level. Finally, it is important to note that there is a 2% to 3% undercount statewide for all votes cast in the 2014 election. Given the missing votes for the 2014 contests in Lorain County, the VTD-level totals in that county were approximated using the official precinct 2014 returns. First, after identifying the township, city, or village of each 2014 precinct, the official precinct-level returns were aggregated up to that level. Those municipality-level returns were then disaggregated for each candidate down to the VTDs in each municipality, proportionally to the vote counts for the candidate running for the same office and party in the 2018 midterm cycle.

- In order to compare the maps in Ohio to other congressional elections across the nation over the past five decades, I examined:
  - A large data set on candidacies and results in Congressional elections: I obtained results from 1972-2018 collected by the Constituency-Level Elections Archive (CLEA) (Kollman et al. 2017). The results from 1972-1990 are based on data collected and maintained by the Inter-university Consortium for Political and Social Research (ICPSR) and adjusted by CLEA. The data from 1992-2018 are based on data collected by CLEA from the Office of the Clerk at the House of the Representatives. I supplemented this dataset with recent election results collected by the MIT Election and Data Science Lab (MIT Election and Data Science Lab 2017) and Dave Leip's Atlas of U.S. Presidential Elections.
  - Data on presidential election returns and incumbency status in Congressional elections. I used data on elections in congressional districts from 1972-2020 collected by Professor Gary Jacobson (University of California, San Diego). This dataset has been used in many Political Science studies and has canonical status in the political science profession (Jacobson 2015).
  - Information on who controlled each redistricting plan in Congressional elections (e.g., Democrats, Republicans, or a Commission) from 1972-2012 assembled by the Brennan Center (Brennan Center 2017).
  - I imputed vote shares and turnout in uncontested districts and then calculated the partisan bias metrics described on pp. 6-14 of this report using the methodology described in Stephanopoulos and Warshaw (2020).

I have previously provided expert reports in five redistricting-related cases:

- Between 2017 and 2019, I provided reports for *League of Women Voters of Pennsylvania v. Commonwealth of Pennsylvania*, No. 159 MM 2017, *League of Women Voters of Michigan* v. *Johnson*, 17-14148 (E.D. Mich), and *APRI et al.* v. *Smith et al.*, No. 18-cv-357 (S.D. Ohio). My testimony was found to be credible in each of these cases and was extensively cited by the judges in their decisions.

- In the current redistricting cycle, I have provided reports in *League of Women Voters* v. *Ohio Redistricting Commission*, No. 2021-1193 and *League of Women Voters* vs. *Kent County Apportionment Commission*.

In addition, I have provided expert testimony and reports in several cases related to the U.S. Census: *State of New York et al.* v. *United States Department of Commerce*, 18-cv-2921 (S.D.N.Y.), *New York* v. *Trump*; *Common Cause* v. *Trump*, 20-cv-2023 (D.D.C.), and *La Union Del Pueblo Entero (LUPE)* v. *Trump*, 19-2710 (D. Md.).

I am being compensated at a rate of $325 per hour. The opinions in this report are my own, and do not represent the views of George Washington University.

3 Summary

Ohio's Congressional redistricting plan was proposed by Republican leaders and passed on party lines, with nearly all Republicans voting in favor and all Democrats opposed.[3] This report examines whether this plan meets the criteria in the Ohio Constitution. Article XIX.01, Section 3(A) of Ohio's Constitution requires that "If the general assembly passes a congressional district plan under division (C)(1) of this section by a simple majority of the members of each house of the general assembly, and not by the vote described in division (C)(2) of this section", then "The general assembly shall not pass a plan that unduly favors or disfavors a political party or its incumbents."

Ohio's Constitutional criteria, which require that congressional districting plans not unduly favor or disfavor a political party, are related to a long-line of Political Science literature on partisan gerrymandering and democratic representation. The relationship between the distribution of partisan support in the electorate and the partisan composition of the government—what Powell (2004) calls "vote–seat representation"—is a critical link in the longer representational chain between citizens' preferences and governments' policies. If the relationship between votes and seats systematically advantages one party over another, then some citizens will enjoy more influence—more "voice"—over elections and political outcomes than others (Caughey, Tausanovitch, and Warshaw 2017).

I use three complementary methodologies to project future election results in order to evaluate whether Ohio's newly enacted Congressional map meets the requirements of Article XIX.01, Section 3(A) in its Constitution. First, I analyze the results of the 2020 Congressional election on the newly enacted map. Second, I use a composite of previous statewide election results between 2012-2020 to analyze the new map.[4] Third, I

3. See Jeremy Pelzer, Cleveland Plain Dealer, November 18, 2021, https://www.cleveland.com/news/2021/11/ohio-legislature-passes-congressional-redistricting-plan-giving-republicans-a-likely-13-2-advantage.html.

4. These include the following elections: 2012 Presidential, 2012 Senate, 2014 gubernatorial, 2014 Secretary of State, 2016 Presidential, 2016 Senate, 2018 Senate, 2018 gubernatorial, 2018 attorney's general, 2018 Secretary of State, 2018 Auditor, 2018 Treasurer, and 2020 Presidential. Geographic data on the other three statewide elections in 2014 is not available. But this probably doesn't affect my results

complement this approach using the open source PlanScore.org website, which is a project of the Campaign Legal Center.[5] PlanScore uses a statistical model to estimate district-level vote shares for a new map based on the relationship between presidential election results and legislative results between 2012-2020.[6] Based on these three approaches, I characterize the bias in Ohio's plans based on a large set of established metrics of partisan fairness. I also place the bias in Ohio's plans into historical perspective. I also analyze whether the map unduly favors incumbents from one party.

All of these analyses indicate an extreme level of pro-Republican bias in Ohio's enacted Congressional plan. There are 10 strongly Republican districts, 2 strongly Democratic districts, and 3 potentially competitive districts, each of which leans toward Republicans. In the average election, Republicans are likely to get about 55% of the statewide vote and about 80% of the seats in Ohio's congressional delegation. Thus, the plan clearly unduly favors the Republican party.

In the actual 2020 congressional election, Democrats received 43% of the two-party vote (and Republicans 57%), but Democrats only won 25% (4) of the seats (and Republicans won 75%). This was already one of the most extreme partisan gerrymanders of a congressional map in modern history (See *APRI et al.* v. *Smith et al.*, No. 18-cv-357 (S.D. Ohio)). Based on the congressional election results, the new plan is even more extreme than the last one. On the new map, Democrats would only win 13% (2) of the seats using the precinct-level results of the 2020 congressional election.

The new plan also displays an extreme level of partisan bias when I evaluate it based on the results of recent statewide elections. In the 2020 presidential election, Democrat Joe Biden received about 46% of the two-party vote.[7] However, he would have only won 27% (4) of the Congressional districts. In the 2018 gubernatorial election, Democrat Richard Cordray did a little bit better. He received about 48% of the two-party vote. Yet again, however, he would have only won 27% of the districts under the enacted plan. In the 2016 presidential election, Democrat Hillary Clinton received about 46% of the two-party vote. But she would have only won 13% of the seats. In the 2012 presidential election, Democratic President Barack Obama received about 52% of the two-party vote. But he would have still won only 40% of the seats.

Based on all the available statewide elections in Ohio between 2012-2020, I find that

much since these elections were similar to the average of the 2014 gubernatorial and Secretary of State elections.

5. I am on the social science advisory board of Plan Score, but do not have any role in PlanScore's evaluation of individual maps.

6. See `https://planscore.campaignlegal.org/models/data/2021C/` for more details.

7. Following standard convention, throughout my analysis I focus on two-party vote shares.

the enacted Congressional plan leads to a much higher Republican share of the seats than their share of the statewide vote. Indeed, across all statewide elections during this period, the Democrats' statewide two-party vote share averaged about 45% of the vote, but they are only likely to win about 26% of the seats.[8]

I reach the same conclusion using the predictive model on the PlanScore website. It indicates that the enacted plan favors Republican candidates in 97% of scenarios. Even though Republicans only get about 56% of the statewide vote in recent elections (and Democrats get 44%), PlanScore analysis indicates that Republicans are expected to win 79% of the seats in Ohio's Congressional delegation (and Democrats would win 21% of the seats).[9] Based on generally accepted Political Science metrics (the Efficiency Gap and the Declination), PlanScore indicates that Ohio's enacted plan would have historically extreme levels of pro-Republican bias. In fact, the pro-Republican bias in Ohio's Congressional plan is larger than 98% of previous plans in the United States from 1972-2020.

Overall, this analysis indicates that the enacted plan unduly favors the Republican party. This conclusion is based on a wide variety of approaches to project future election results and to estimate the partisan bias of the plan. Regardless of the approach I use, it is clear that the enacted map has an extreme level of bias in favor of the Republican party.

The enacted plan also favors incumbents from the Republican Party. It puts two of the four Democratic incumbents from the previous plan into largely new districts that will now have a majority of Republican voters. It does not put any Republican incumbent into a district with a majority of Democratic voters. This bias against Democratic incumbents is especially clear in the case of Representative Marcy Kaptur. In 2020, she comfortably won reelection with 63% of the two-party vote. The new plan slices her old district into five districts. On the new map, she would have only won about 46% in the 2020 House election, and thus would likely lose in 2022.

4 Background on Partisan Gerrymandering

The goal of partisan gerrymandering is to create legislative districts that are as "efficient" as possible in translating a party's vote share into seat share (McGhee 2014, 2017; Caughey, Tausanovitch, and Warshaw 2017). In practice, this entails drawing districts in which the supporters of the advantaged party constitute either a slim majority (e.g., 55%

8. I weight the composite scores to give each election cycle equal weight in the index. The seat-level projections are based on the 13 statewide elections where I have precinct-level data.

9. This is a probabilistic estimate based on 1000 simulations of possible elections using a model of the elections between 2012-2020.

of the two-party vote) or a small minority (e.g., 20%). The former is achieved by "cracking" local opposing-party majorities across multiple districts and the latter by "packing" them into a few overwhelming strongholds. In a "cracked" district, the disadvantaged party narrowly loses, while in a "packed" district, the disadvantaged party wins overwhelmingly (Buzas and Warrington 2021). The resulting *asymmetry* or *advantage* in the efficiency of the vote–seat relationships of the two parties lies at the core of normative critiques of partisan gerrymandering. Asymmetries in the translation of votes to seats "offer a party a means of increasing its margin of control over policy without winning more votes from the public" (McGhee 2014).

In addition to creating a plan that skews the vote-seat curve toward their party, the advantaged party also often seeks to build a map that is *insulated* against changes in the public's preferences. This type of unresponsive map enables the advantaged party to continue to win the majority of seats even in the face of large gains in the disadvantaged party's statewide vote share. It ensures that the gerrymander is durable over multiple election cycles.

There are a number of approaches that have been proposed to measure partisan advantage in a districting plan. These approaches focus on asymmetries in the efficiency of the vote–seat relationships of the two parties. In recent years, at least 10 different approaches have been proposed (McGhee 2017). While no measure is perfect, much of the recent literature has focused on a handful of related approaches that I describe below.

4.1 Efficiency Gap

Both cracked and packed districts "waste" more votes of the disadvantaged party than of the advantaged one (McGhee 2014; Stephanopoulos and McGhee 2015).[10] This suggests that gerrymandering can be measured based on asymmetries in the number of wasted votes for each party. The *efficiency gap* (EG) focuses squarely on the number of each party's wasted votes in each election. It is defined as "the difference between the parties' respective wasted votes, divided by the total number of votes cast in the election" (Stephanopoulos and McGhee 2015, 831; see also McGhee 2014, 2017).[11] All of the losing

10. The authors of the efficiency gap use the term "waste" or "wasted" to describe votes for the losing party and votes for the winning party in excess of what is needed to win an election. Since the term is used by the efficiency gap authors, I use it here when discussing the efficiency gap.

11. The efficiency gap calculations here focus on wasted votes in *congressional elections* since these results directly capture voters' preferences in these elections. However, we might also calculate the efficiency gap using district-level results from presidential elections or other statewide races. These have the "advantage of being (mostly) unaffected by district-level candidate characteristics" (Stephanopoulos and McGhee 2015, 868). This feature is particularly useful for simulating efficiency gaps from randomly generated districting plans since candidate characteristics are clearly influenced by the final districting

ADAMS_00030

party's votes are wasted if they lose the election. When a party wins an election, the wasted votes are those above the 50%+1 needed to win.

If we adopt the convention that positive values of the efficiency gap imply a Democratic advantage in the districting process and negative ones imply a Republican advantage, the efficiency gap can be written mathematically as:

$$EG = \frac{W_R}{n} - \frac{W_D}{n} \tag{1}$$

where W_R are wasted votes for Republicans, W_D are wasted votes for Democrats, and n is the total number of votes in each state.

Table 1 provides a simple example about how to calculate the efficiency gap with three districts where the same number of people vote in each district. In this example, Democrats win a majority of the statewide vote, but they only win 1/3 seats. In the first district, they win the district with 75/100 votes. This means that they only wasted the 24 votes that were unnecessary to win a majority of the vote in this district. But they lose the other two districts and thus waste all 40 of their votes in those districts. In all, they waste 104 votes. Republicans, on the other hand, waste all 25 of their votes in the first district. But they only waste the 9 votes unnecessary to win a majority in the two districts they win. In all, they only waste 43 votes. This implies a pro-Republican efficiency gap of $\frac{43}{300}$ - $\frac{104}{300}$= -20%.

Table 1: Illustrative Example of Efficiency Gap

District	Democratic Votes	Republican Votes
1	75	25
2	40	60
3	40	60
Total	155 (52%)	145 (48%)
Wasted	104	43

In order to account for unequal population or turnout across districts, the efficiency gap formula in equation 1 can be rewritten as:

$$EG = S_D^{margin} - 2 * V_D^{margin} \tag{2}$$

plan. Presidential elections or other statewide races are less closely tied, however, to voters' preferences in legislative races given the district lines that actually exist. In practice, though, both legislative races and other statewide races produce similar efficiency gap results for modern elections where voters are well sorted by party and ideology. Indeed, the data indicate that the correlation between efficiency gap estimates based on congressional elections and presidential elections is approximately 0.8 for elections held after 2000 and about 0.9 for elections held after the 2011 redistricting cycle.

ADAMS_00031

where S_D^{margin} is the Democratic Party's seat margin (the seat share minus 0.5) and V_D^{margin} is is the Democratic Party's vote margin. V_D^{margin} is calculated by aggregating the raw votes for Democratic candidates across all districts, dividing by the total raw vote cast across all districts, and subtracting 0.5 (McGhee 2017, 11-12). In the example above, this equation also provides an efficiency gap of -20% in favor of Republicans. But it could lead to a slightly different estimate of the efficiency gap if districts are malapportioned or there is unequal turnout across districts.[12]

In the case of Ohio's enacted Congressional map, equation 2 implies there would have been a pro-Republican efficiency gap of approximately 23% using the votes from the 2020 election re-aggregated onto the enacted plan. This is a larger pro-Republican Efficiency Gap than 99% of previous congressional plans with more than 6 seats over the past 50 years.

The efficiency gap mathematically captures the packing and cracking that are at the heart of partisan gerrymanders (Buzas and Warrington 2021). It measures the extra seats one party wins over and above what would be expected if neither party were advantaged in the translation of votes to seats (i.e., if they had the same number of wasted votes). A key advantage of the efficiency gap over other measures of partisan bias is that it can be calculated directly from observed election returns even when the parties' statewide vote shares are not equal.

4.2 Declination

Another measure of asymmetries in redistricting plans is called *declination* (Warrington 2018b, 2018a). The declination metric treats asymmetry in the vote distribution as indicative of partisan bias in a districting plan (Warrington 2018a). If all the districts in a plan are lined up from the least Democratic to the most Democratic, the mid-point of the line formed by one party's seats should be about as far from the 50 percent threshold for victory on average as the other party's (McGhee 2018).

Declination suggests that when there is no gerrymandering, the angles of the lines (θ_D and θ_R) between the mean across all districts and the point on the 50% line between the mass of points representing each party will be roughly equal. When they deviate from each other, the smaller angle (θ_R in the case of Ohio) will generally identify the favored party. To capture this idea, declination takes the difference between those two angles (θ_D

12. In general, the two formulations of the efficiency gap formula yield very similar results. Because Democrats tend to win lower-turnout districts, however, the turnout adjusted version of the efficiency gap in equation 2 tends to produce results that suggest about a 2% smaller disadvantage for Democrats than the version in Equation 1 (see McGhee 2018).

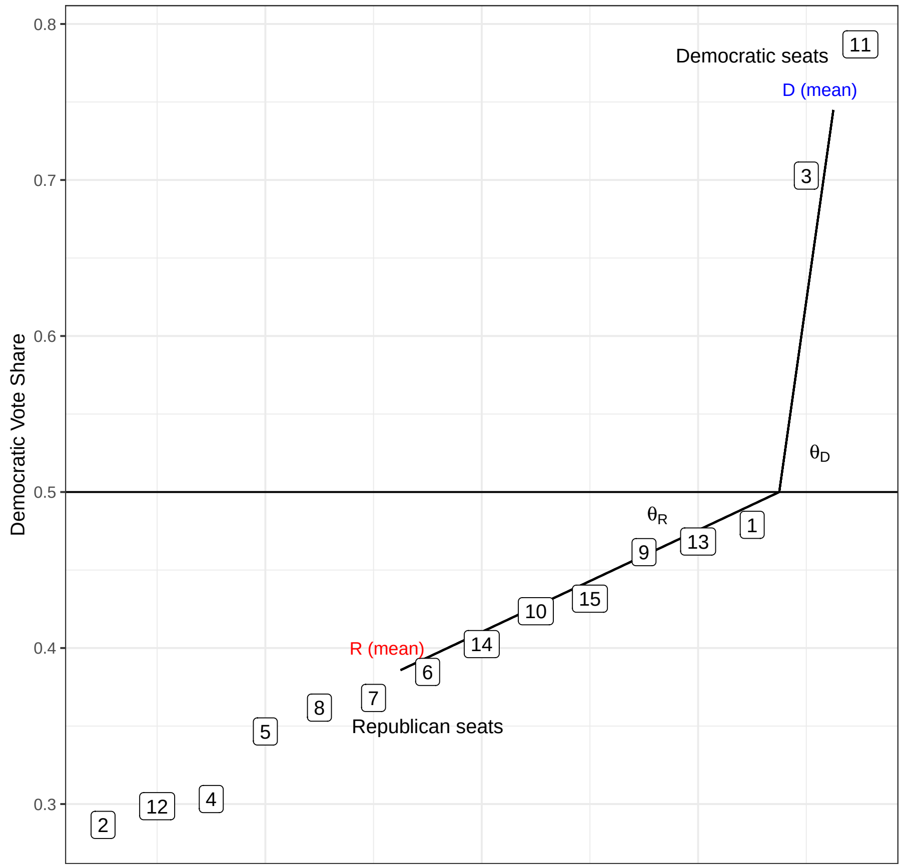

Figure 1: Plot illustrating declination based on votes in 2020 Congressional election re-aggregated to new plan

and θ_R) and divides by $\pi/2$ to convert the result from radians to fractions of 90 degrees.[13] This produces a number between -1 and 1. As calculated here, positive values favor Democrats and negative values favor Republicans. Warrington (2018b) suggests a further adjustment to account for differences in the number of seats across legislative chambers. I use this adjusted declination estimate in the analysis that follows.[14]

In the case of Ohio's 2020 congressional elections, the declination metric indicates that the plan has a pro-Republican bias of .90. This is a larger absolute level of bias than 97% of previous congressional elections in states with more than 6 seats, and more pro-Republican than 97% of previous plans.

13. This equation is: $\delta = 2^*\ (\theta_R - \theta_D)\ /\ \pi$.

14. This adjustment uses this equation: $\hat{\delta} = \delta * \ln(\text{seats}) / 2$

ADAMS_00033

4.3 Mean-median Gap

Another metric that some scholars have proposed to measure partisan bias in a districting plan is the *mean-median gap*: the difference between a party's vote share in the median district and their average vote share across all districts. If the party wins more votes in the median district than in the average district, they have an advantage in the translation of votes to seats (Krasno et al. 2018; Best et al. 2017; Wang 2016). In statistics, comparing a dataset's mean and median is a common statistical analysis used to assess skews in the data and detect asymmetries (Brennan Center 2017).

The mean-median difference is very easy to apply (Wang 2016). It is possible, however, for packing and cracking to occur without any change in the mean-median difference (Buzas and Warrington 2021). That is, a party could gain seats in the legislature without the mean-median gap changing (McGhee 2017).[15] It is also sensitive to the outcome in the median district (Warrington 2018b). In addition, the mean-median difference lacks a straightforward interpretation in terms of the number of seats that a party gains through gerrymandering. Finally, the assumptions of the mean-median gap are less tenable in less electorally competitive states.

District	Democratic Vote Share
2	0.29
12	0.30
4	0.30
5	0.35
8	0.36
7	0.37
6	0.38
14	0.40
10	0.42
15	0.43
9	0.46
13	0.47
1	0.48
3	0.70
11	0.79
Mean	43.4%
Median	40.3%

Table 2: Results in 2020 Ohio Congressional Elections Re-Aggregated onto Enacted Map

15. As McGhee (2017), notes, "If the median equals the win/loss threshold–i.e., a vote share of 0.5–then when a seat changes hands, the median will also change and the median- mean difference will reflect that change. But if the median is anything other than 0.5, seats can change hands without any change in the median and so without any change in the median-mean difference." See also Buzas and Warrington (2021) who make a similar point using simulated packing and cracking.

ADAMS_00034

Table 2 illustrates the mean-median approach using the results in the 2020 Ohio congressional elections re-aggregated to the districts in the enacted map. In the actual 2020 congressional elections, Democrats won 4 seats. But on the enacted plan, Democrats would only have won 2 seats. Moreover, Table 2 shows that many Democratic voters were packed into just 2 districts where the Democratic candidates won by overwhelming margins. The remaining Democratic voters were cracked across the other districts. This table shows the disproportionate percentage of the statewide vote that Democrats would have needed to win a majority of Ohio's congressional seats in 2020. Across all districts, Democrats won an average of 43.4% of the vote. But they only won 40.3% in the median district. This translated into a pro-Republican mean-median difference of 3.1%.

4.4 Symmetry in the Vote-Seat Curve Across Parties

Basic fairness suggests that in a two-party system each party should receive the same share of seats for identical shares of votes. The *symmetry* idea is easiest to understand at an aggregate vote share of 0.5—a party that receives half the vote ought to receive half the seats—but a similar logic can apply across the "seats- votes curve" that traces out how seat shares change as vote shares rise and fall. For example, if a party receives a vote share of 0.57 and a seat share of 0.64, the opposing party should also expect to receive a seat share of 0.64 if it were to receive a vote share of 0.57. An unbiased system means that for V share of the votes a party should receive S share of the seats, and this should be true for all parties and vote percentages (Niemi and Deegan 1978; Gelman and King 1994a; McGhee 2014; Katz, King, and Rosenblatt 2020).

Gelman and King (1994a, 536) propose two ways to measure partisan bias in the symmetry of the vote-seat curve. First, it can be measured using counter-factual election results in a range of statewide vote shares between .45 and .55. Across this range of vote shares, each party should receive the same number of seats. Symmetry captures any departures from the standard that each party should receive the same seat share across this range of plausible vote shares. For example, if partisan bias is -0.05, this means that the Democrats receive 5% fewer seats in the legislature than they should under the symmetry standard (and the Republicans receive 5% more seats than they should).

To illustrate the symmetry metric, Table 3 calculates what each party's share of the seats would have been in Ohio's 2020 Congressional elections (re-aggregated onto the enacted map) across a range of statewide vote shares from 45%-55%. It shows that Democrats only received a third or less of the seats in most of the scenarios where they received less than 50% of the votes. This might not have been problematic under the

ADAMS_00035

symmetry standard if Republicans also only received a third of the seats when they received less than 50% of the votes. However, Table 3 shows that Republicans still would have received half of the seats even when they won a minority of the votes. Across this range of statewide vote shares from 45%-55%, Democrats receive an average of 39% of the seats (and Republicans win 61%). This implies a partisan bias of 11% using the symmetry metric. That is, Republicans won 11 percentage points more of the seats than they would have won if the seat-vote curve was symmetric between the two parties.

Dem. Vote Share	Dem. Seat Share	Rep. Vote Share	Rep. Seat Share
45%	13%	55%	87%
46%	20%	54%	80%
47%	33%	53%	67%
48%	33%	52%	67%
49%	33%	51%	67%
50%	40%	50%	60%
51%	47%	49%	53%
52%	47%	48%	53%
53%	53%	47%	47%
54%	53%	46%	47%
55%	60%	45%	40%
Mean Seat Share	39%		61%
Bias	-11%		11%

Table 3: Symmetry Calculations for 2020's Congressional Elections Re-Aggregated onto Enacted Map

The symmetry metric is closely related to the efficiency gap. In the special case where each party receives half of the statewide vote, the symmetry and the efficiency gap metrics are mathematically identical (Stephanopoulos and McGhee 2015, 856). More generally, the symmetry and efficiency gap yield very similar substantive results when each party's statewide vote share is close to 50% (as is the case in Ohio). When elections are uncompetitive, however, and one party wins a large percentage of the statewide vote, the efficiency gap and these symmetry metrics are less correlated with one another (857).

A weakness of the symmetry approach is that it requires the analyst to calculate counterfactual elections. This approach has both conceptual and empirical limitations. At a conceptual level, it is not clear that it aligns perfectly with the usual definition of a gerrymander. Indeed, "when observers assert that a district plan is a gerrymander, they usually mean that it systematically benefits a party (and harms its opponent) in actual elections. They do not mean that a plan would advantage a party in the hypothetical event of a tied election, or if the parties' vote shares flipped" (Stephanopoulos and McGhee 2015, 857). At an empirical level, in order to generate symmetry metrics, we need to simulate counter-factual elections by shifting the actual vote share in each district a uniform amount (McGhee 2014).[16] In general, this uniform swing assumption seems reasonable based on past election results (though is probably less reasonable in less competitive states). Moreover, it has been widely used in past studies of redistricting. But there is no way to conclusively validate the uniform swing assumption for any particular election.

An important strength, however, of the symmetry approach is that it is based on the shape of the seats-votes curve and not any particular point on it. As a result, it is relatively immune to shifts in party performance (McGhee 2014). For instance, the bias toward Republicans in Ohio's symmetry metric was very similar in 2012-2020. Moreover, the symmetry approach has been very widely used in previous studies of gerrymandering and redistricting (Gelman and King 1994a; McGhee 2014). Overall, the symmetry approach is useful for assessing partisan advantage in the districting process.

4.5 Comparison of Partisan Bias Measures

All of the measures of partisan advantage discussed in the previous sections are closely related both theoretically and empirically (McGhee 2017; Stephanopoulos and McGhee 2018). Broadly speaking, all of the metrics consider how votes between the two parties are distributed across districts (Warrington 2018a). For example, the efficiency gap is mathematically equivalent to partisan bias in tied statewide elections (Stephanopoulos and McGhee 2018). Also, the median-mean difference is similar to the symmetry metric, since any perfectly symmetric seats-votes curve will also have the same mean and median (McGhee 2017).

Second, each of the concepts are closely related empirically, particularly in states with competitive elections. Figure 2 shows the correlation between each measure. The various measures have high correlations with one another.[17] Moreover, most of the variation in the metrics can be summarized on a single latent dimension (Stephanopoulos and McGhee 2018; Stephanopoulos and Warshaw 2020). So, overall, while there may be occasional

16. In principle, the uniform swing election could be relaxed, and swings could be estimated on a district-by-district basis. But this is rarely done in practice since it would require a much more complicated statistical model, and probably would not improve estimates of symmetry very much.

17. While each measure is highly correlated with one another, the efficiency gap and declination measures are particularly closed related and the symmetry and mean-median measures are very closely related. This could be because the efficiency gap and the declination consider the seats actually won by each party, while the symmetry metric and the mean-median difference do not (Stephanopoulos and McGhee 2018, 1557). In addition, the efficiency gap and the declination appear to best capture the packing and cracking that characterize partisan gerrymandering (Buzas and Warrington 2021).

ADAMS_00037

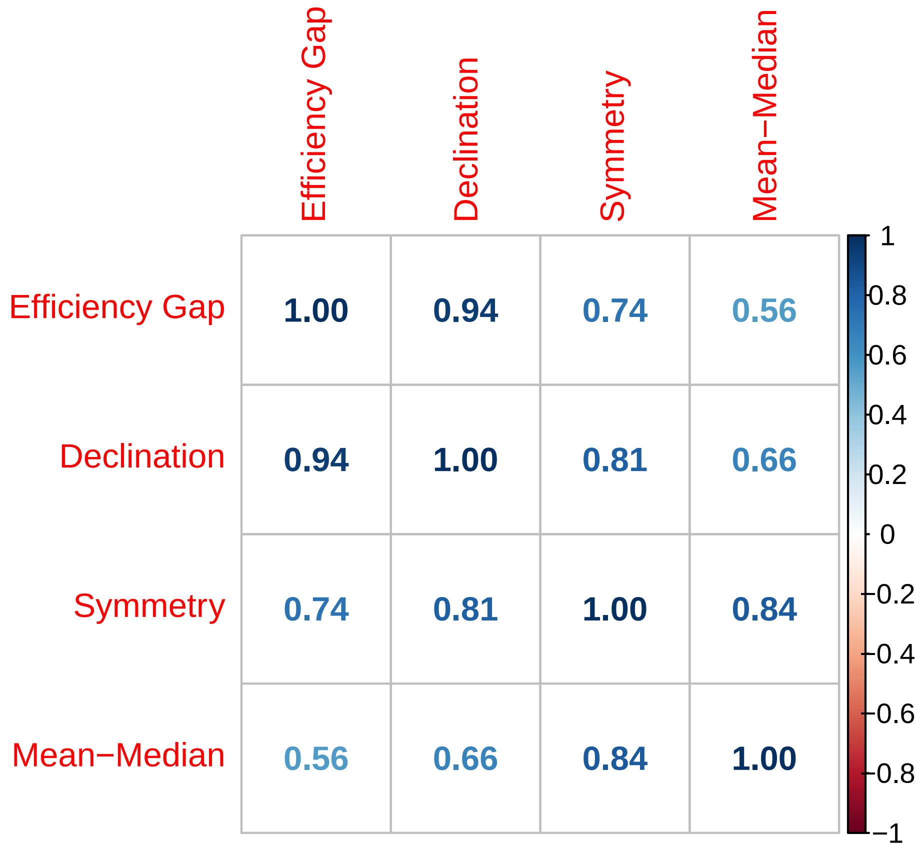

Figure 2: Correlation between measures of partisan bias in states.

cases where the metrics disagree about the amount of bias in a particular plan, the various metrics usually yield similar results for the degree of partisan bias in a districting plan (Nagle 2015). Where none of the metrics is an outlier and they all point in the same direction, we can draw a particularly robust conclusion.

While all the metrics are useful for summarizing partisan bias in a districting plan, Buzas and Warrington (2021) shows that the efficiency gap and the declination capture the packing and cracking that characterize partisan gerrymandering extremely well. In contrast, "partisan bias and mean-median difference are unable to consistently record simulated packing and cracking... As a result, we recommend that neither partisan bias nor the mean-median difference be used for the "outlier" or "ensemble" method, where it is crucial that more extreme values of the measure indicate more extreme levels of partisan gerrymandering." Moreover, McGhee (2017, 9) shows that the assumptions of the symmetry and mean-median measures become progressively less plausible as the statewide vote shares in a plan move away from 50% (McGhee 2017, 9). In my analysis below, I generally show all four metrics. But I particularly focus on the efficiency gap and declination since these best capture packing and cracking, and these metrics are best suited for a state such as Ohio where there is typically about a 45-55 split of the two-party vote in statewide elections.

4.6 Responsiveness and Competitive Elections

Another benchmark for a districting plan is the percentage of districts likely to have competitive elections under that plan and the responsiveness of the plan to changes in voters' preferences (Cox and Katz 1999). There are a number of normative reasons to care about the number of competitive districts in a plan. First, this affects the responsiveness of a map as the two parties' statewide vote shares rise and fall. A plan with more competitive elections is likely to be more responsive to changes in voters' preferences than a plan with fewer competitive elections (McGhee 2014). An unresponsive map ensures that the bias in a districting plan toward the advantaged party is insulated against changes in voters' preferences, and thus is durable across multiple election cycles. Second, uncompetitive districts tend to protect incumbents from electoral sanctions (Tufte 1973; Gelman and King 1994a). This could harm political representation by making legislators less responsive and accountable to their constituents' preferences.

To illustrate the concept of responsiveness, Figure 3 shows the vote-seat curve in Ohio generated by applying uniform swings to the 2020 election results.[18] Specifically, I apply a uniform swing in the actual election results until I achieve an average Democratic vote share of 40%. Then I steadily increase the average Democratic vote share until it reaches 60%. Figure 3 indicates that Republicans win two thirds or more of the seats across all of the range of actual election swings over the past decade.

There are a couple of approaches we might use to evaluate whether individual districts on a plan are likely to have competitive elections. We could measure whether a district was competitive in an election based on whether the winning party received less than 55% of the two-party vote (Fraga and Hersh 2018; Jacobson and Carson 2015, 91).[19] While this definition is sometimes used in the literature, though, it is not clear that a sharp threshold at 55% is the best measure of competitiveness.

Another possible definition of competitiveness might be whether a district is likely

18. The layout of this chart is adapted from charts in Royden, Li, and Rudensky (2018).

19. Fraga and Hersh (2018) justify this definition based on the fact that the Cook Political Report's "median 'leaning' race ended up with a vote margin of 10 percentage points (a 55%–45% race)."

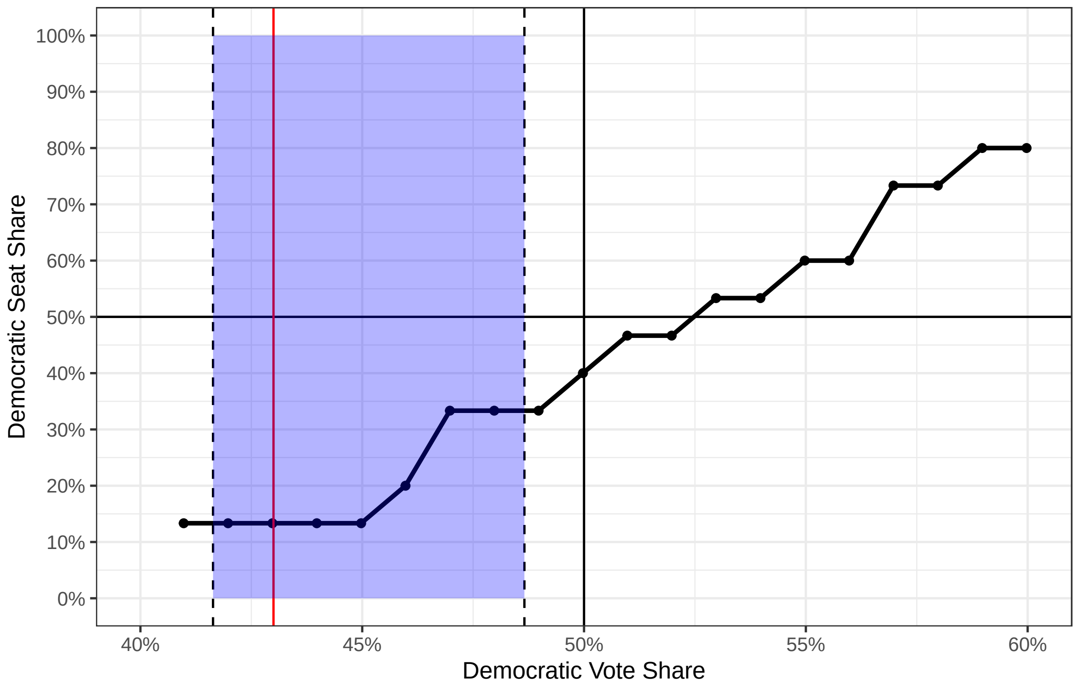

Figure 3: Vote-seat curve in Ohio using uniform swings in 2020 election results re-aggregated using enacted plan. The shaded area shows the range between the minimum and maximum Democratic statewide vote share in congressional elections from 2012-2020. The red line shows the actual Democratic statewide vote share in the 2020 House elections.

to switch parties at least once per decade (Henderson, Hamel, and Goldzimer 2018). This definition is more empirically robust because it is not dependent on any particular electoral threshold for competitiveness. Indeed, in a state with swing voters where the two parties' statewide shares vary substantially over the course of the decade, a district where the winning party normally wins 56% of the vote could be competitive. In another state with few swing voters and very inelastic election results, a district where the winning party normally wins 53% of the vote might not even be competitive.

4.7 Partisan Control of the Redistricting Process and Gerrymandering

While many factors could influence the degree of partisan advantage in the districting process,[20] there is a wide body of evidence from previous studies that control of the re-districting process has a large effect on partisan advantage in subsequent elections carried

20. Partisan advantage in the districting process can differ across states for reasons unrelated to the drawing of district lines, such as variation in how groups are distributed across geography (Chen and Rodden 2013). It can also be affected by goals other than maximizing partisan seat share, such as representation of racial minorities (e.g., Brace, Grofman, and Handley 1987).

ADAMS_00040

out under a given plan. Cox and Katz (2002) show that Democratic control of the redistricting process in many states during the 1960s led to a lasting partisan advantage for Democrats in House elections. More generally, Gelman and King (1994b) find that the party in control of redistricting shifts outcomes in its favor, and that "the effect is substantial and fades only very gradually over the following 10 years" (543). This result has been confirmed in numerous recent articles. McGhee (2014) finds that "parties seek to use redistricting to shift bias in their favor and that they are successful in these efforts" (74).[21] Finally, Stephanopoulos (2018) shows that partisan control of the districting process has a substantial effect on the efficiency gap.[22] This past literature indicates that districting plans passed by one political party with unified control of government, as in Ohio, often unduly favor that party.

5 Partisan Bias in Ohio's Enacted Congressional Map

In this section, I will provide a comprehensive evaluation of the partisan fairness of Ohio's enacted congressional districting plan (see Figure 4 for a map of the enacted plan). In order to evaluate the enacted plan, we need to predict future election results on this map. Unfortunately, there is no way to know, with certainty, the results of future elections. Thus, I use three complementary methodologies to predict future congressional elections in Ohio and generate the various metrics I discussed earlier.

Figure 4: Map of Enacted Congressional Districts from PlanScore.org

21. McGhee (2014) finds that partisan control affects the districting process using both the Gelman and King (1994b) measure of partisan symmetry and the efficiency gap as outcome variables.

22. He shows that states with unified Republican control have about 5 percentage points more pro-Republican efficiency gaps than states with split control, and states with unified Democratic control have about 3 percentage points more pro-Democratic efficiency gaps than states with split control.

5.1 2020 Congressional election results

First, I use the 2020 precinct-level congressional results on both the 2012-20 map and re-aggregated to the enacted map to estimate the various metrics. This approach implicitly assumes that future elections will look like the 2020 election. These endogenous election are likely to be an excellent predictor of future voting patterns in congressional elections. Based on these results, Republicans would win 57% of the votes, but 87% of the seats on the enacted plan. In other words, Republicans would win thirty percentage points more seats than votes.

Metric	Value	More Biased than this % Historical Plans	More Pro-Republican than this % Historical Plans
2012-2020 Plan			
Republican Seat Share	75%		
Efficiency Gap	-11%	78%	91%
Declination	-.51	85%	91%
Mean-Median Diff	-4%	57%	78%
Symmetry Bias	-12%	78%	87%
Average		75%	87%
Enacted Plan			
Republican Seat Share	87%		
Efficiency Gap	-23%	98%	99%
Declination	-.90	97%	97%
Mean-Median Diff	-3%	42%	72%
Symmetry Bias	-10%	69%	83%
Average		77%	88%

Table 4: Partisan bias metrics for Congressional plan based on 2020 Congressional election results re-aggregated onto enacted map

The average efficiency gap of the enacted plan based on the precinct-level 2020 House results is -23% (see Table 4). This is more extreme than 98% of previous plans and more pro-Republican than over 99% of previous plans. The enacted plan is more pro-Republican than 97% of prior plans in the country using the declination metric. The other metrics also show that Ohio's enacted plan has a large pro-Republican bias. When we average across all four metrics, the plan is more extreme than 77% of previous plans and more pro-Republican than 88% of previous plans.

5.2 Composite of previous statewide elections

Next, I use a composite of previous statewide election results between 2012-2020 re-aggregated to the enacted map.[23] For each year, I estimate each party's vote share, seat share, and the average of the partisan bias metrics across races. I then average them together to produce a composite result. This approach implicitly assumes that future voting patterns will look like the average of these recent statewide elections.

		2012-2020 Composite	
Metric	Value	> Biased than this % Plans	> Pro-Rep. than this % Plans
2012-2020 Plan			
Republican Seat Share	75%		
Efficiency Gap	-15%	90%	96%
Declination	-.54	88%	93%
Mean-Median	-4%	47%	74%
Symmetry Bias	-19%	94%	95%
Average		80%	89%
Enacted Plan			
Republican Seat Share	74%		
Efficiency Gap	-14%	87%	95%
Declination	-.54	88%	92%
Mean-Median	-2%	28%	65%
Symmetry Bias	-13%	81%	88%
Average		70%	85%

Table 5: Composite bias metrics for enacted Congressional plan based on statewide elections

When I average across these statewide elections from 2012-2020, Democrats win 45% of the votes and 26% of the seats (see Table 5). The average efficiency gap of the enacted plan based on these previous election results is -14%. This is more extreme than 87% of previous plans and more pro-Republican than 95% of previous plans. The enacted plan is also more pro-Republican than 92% of previous plans using the declination metric. The mean-median and symmetry also show that Ohio's enacted plan has a substantial pro-Republican bias. When I average across all four metrics, the plan is more extreme than 70% of previous plans and more pro-Republican than 85% of previous plans.[24]

23. These include the following elections: 2012 Presidential, 2012 Senate, 2014 gubernatorial, 2014 Secretary of State, 2016 Presidential, 2016 Senate, 2018 Senate, 2018 gubernatorial, 2018 attorney's general, 2018 Secretary of State, 2018 Auditor, 2018 Treasurer, and 2020 Presidential. Geographic data on the other three statewide elections in 2014 is not available. But this probably doesn't affect my results much since these elections were similar to the average of the 2014 gubernatorial and Secretary of State elections. I weight the elections so that each year is given equal weight in the composite.

24. In the Appendix, I show that I reach very similar results using a variety of other combinations of past elections to construct the composite index.

5.3 PlanScore

Third, I evaluate the enacted plan using a predictive model from the PlanScore.org website. PlanScore uses a statistical model of the relationship between districts' latent partisanship and election outcomes. This enables it to estimate district-level vote shares for a new map and the corresponding partisan gerrymandering metrics.[25] It then calculates various partisan bias metrics. In this case, PlanScore provides estimates of the efficiency gap and declination.[26]

PlanScore also indicates that the enacted Congressional plan has a substantial pro-Republican bias (Table 6). According to PlanScore, the enacted plan has a pro-Republican efficiency gap of 16%. The enacted plan favors Republicans in 99% of the scenarios estimated by PlanScore.[27] Moreover, it is more extreme than 96% of previous plans and more pro-Republican than 98% of previous plans.

Metric	Value	Favors Rep's in this % of Scenarios	More Biased than this % Historical Plans	More Pro-Republican than this % Historical Plans
2012-2020 Plan				
Republican Seat Share	74%			
Efficiency Gap	-12%	96%	90%	97%
Declination	-.42	95%	87%	93%
Average		96%	89%	95%
Enacted Plan				
Republican Seat Share	79%			
Efficiency Gap	-16%	99%	97%	97%
Declination	-.58	99%	95%	98%
Average		99%	96%	98%

Table 6: PlanScore partisan bias metrics for enacted Congressional plan

5.4 Competitiveness of Districts

In their summary of the enacted plan, the Ohio state legislature asserted that "the plan contains six Republican-leaning districts, two Democratic-leaning districts, and seven competitive districts. The number of competitive districts in the plan significantly exceeds the number of competitive districts contained in Ohio's current plan."[28] In this section, I

25. See `https://planscore.campaignlegal.org/models/data/2021C/` for more details.

26. The partisan symmetry and mean-median difference scores are only shown when the parties' statewide vote shares fall between 45% and 55% because outside this range the metrics' assumptions are less plausible (McGhee 2017, 9). In the PlanScore model, the Democrats' two-party vote share is just below 45%.

27. See `https://planscore.campaignlegal.org/plan.html?20211127T135358.249351808Z`

28. See `https://www.legislature.ohio.gov/download?key=17868&format=pdf`. It is important to note the analysis underlying this assertion only includes federal statewide elections, which is an odd set

ADAMS_00044

analyze the accuracy of this statement.

I use a variety of approaches to estimate the number of competitive districts in both the 2012-20 congressional plan and the enacted plan (see Table 7). None of these approaches, however, indicate there are seven competitive districts in the enacted plan. Instead, they indicate there are approximately three competitive districts. Moreover, none of these approaches indicate that the number of competitive districts significantly exceeds the number of competitive districts contained in Ohio's 2012-20 plan. On average, my analysis indicates that the enacted plan has just one more competitive district than the 2012-2020 plan. As a result, I find that the state legislature's claims regarding the competitive districts on the enacted plan are inaccurate.

Data:	2020 House Results		Composite (2012-20)	PlanScore			**Mean**
Metric:	45-55	Historical Swing	45-55	45-55	20%+ Prob. of Each Party Win.	50%+ Prob. Flip in Dec.	
Plan	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2012-20 Plan	2	1	1	3	2	5	2
Enacted Plan	3	3	3	4	2	4	3

Table 7: Number of competitive districts using various data sources and metrics.

First, I use the actual 2020 House results to examine the number of competitive districts. In column 1 of Table 7, I begin by tallying the number of districts where each party's two-party vote share was between 45 and 55%. This approach indicates there are 2 competitive districts on the 2012-20 plan and 3 competitive districts on the enacted plan. As I discussed earlier, however, it is not clear that a sharp threshold at 55% is the best measure of competitiveness.

Based on the approach in Henderson, Hamel, and Goldzimer (2018, Appendix, p. 2), we can also define competitiveness based on whether a district is likely to switch parties at least once per decade based on the maximal swing in the two-party vote. In column 2 of Table 7, I use this approach to tally the number of districts that each party would win at least once over the course of the decade based on the historical range of statewide election results between 2012-2020. Specifically, I conduct a uniform swing to simulate what would happen if the 2020 congressional election were held in the best year for Democrats (2012).[29] I then examine the number of districts that would have been

of elections to focus on. First, this composite does not include the Republican wave year in 2014, but it does include the Democratic wave year in 2018. It also includes two elections from 2012, which implicitly heavily weights this election in the index.

29. It is worth noting, however, that 2012 appears to have been a high-water mark for Democrats in Ohio, and their electoral performance has not come close to this level in subsequent elections.

won at least once by each party. This approach indicates there was 1 competitive district on the 2012-20 plan and 3 competitive districts on the enacted plan.

Next, I use a composite of the 2012-2020 statewide election results to estimate the number of competitive districts. Once again, in column 3 of Table 7, I tally the number of districts where each party's two-party vote share was between 45 and 55%. This approach indicates there was 1 competitive district on the 2012-20 plan and 3 competitive districts on the enacted plan.

Lastly, I use PlanScore to estimate the potential competitiveness of individual districts on the enacted plan. In column 4 of Table 7, I show the number of districts where PlanScore estimates that each party's two-party vote share is expected to be between 45 and 55%. This approach indicates there were 3 competitive districts on the 2012-20 plan and 4 competitive districts on the enacted plan.

It is also possible to use PlanScore to evaluate whether a district is likely to switch parties at least once per decade (Henderson, Hamel, and Goldzimer 2018). PlanScore conducts 1,000 simulations of possible electoral scenarios based on the results of the 2012-2020 congressional and state legislative elections in every state. Using these simulations, PlanScore provides an estimate of the probability that each party will win each seat as well as whether they are likely to have at least a 50% chance of winning each seat once over the course of the decade. In column 5 of Table 7, I estimate the number of districts where each party has at least a 20% chance of winning according to PlanScore. This approach indicates there were 2 competitive districts on the 2012-20 plan and 2 competitive districts on the enacted plan. In column 6 of Table 7, I conduct a similar analysis where I tally the number of districts that each party would have at least a 50% chance of winning at least once over the course of the decade. This approach indicates there are 5 competitive districts on the 2012-20 plan and 4 competitive districts on the enacted plan.

Finally, column 7 of Table 7 averages across all of these approaches. It indicates there are about 2 competitive districts on the 2012-2020 plan and 3 competitive seats on the enacted plan. Thus, there is neither support for the notion that there are seven competitive districts nor that the the enacted plan yields significantly more competitive districts than the 2012-20 plan.

Moreover, it is important to note that the fact that there are about three potentially competitive districts on the enacted plan does not mean that each party has a 50-50 chance at winning these districts. In fact, Republicans are favored in each of these districts and heavily favored in several of them. We can see this using each of the predictive approaches I've used in this report that are summarized in Table 8. The table shows that none of the competitive districts (shown in grey) lean toward Democrats. Indeed, the Republican

District	House 2020	Composite (2012-2020)	PlanScore	Average Dem. Share	Probability Dem. Wins (PlanScore)
	Projected Democratic Vote Share				
1	0.48	0.46	0.48	0.47	36%
2	0.29	0.33	0.30	0.30	1%
3	0.70	0.66	0.70	0.69	99%
4	0.30	0.31	0.31	0.31	1%
5	0.35	0.38	0.35	0.36	1%
6	0.38	0.44	0.36	0.40	1%
7	0.37	0.40	0.38	0.39	1%
8	0.36	0.36	0.36	0.36	1%
9	0.46	0.49	0.45	0.47	16%
10	0.42	0.45	0.46	0.44	18%
11	0.79	0.77	0.76	0.77	99%
12	0.30	0.36	0.32	0.33	1%
13	0.47	0.48	0.48	0.47	31%
14	0.40	0.44	0.42	0.42	4%
15	0.43	0.43	0.44	0.44	13%

Table 8: Democratic Vote Share Projections for Each District on Enacted Plan using a Variety of Methods. Competitive districts in grey.

candidate is likely to win District 1 by 5%, District 9 by 7%, and District 13 by 5%.[30] So Republicans are likely to win all, or nearly all, of these districts in the average election (see right-most column in Table 8). This is especially true if Republicans also have an incumbency advantage in most of these districts (see Jacobson 2021, for more on the incumbency advantage in 2020). Overall, 13 of the 15 districts on the enacted plan lean toward Republicans.

6 Incumbency

Article XIX.01, Section 3(A) of Ohio's Constitution requires that "The general assembly shall not pass a plan that unduly favors or disfavors a political party or its incumbents" (emphasis added). In previous sections of this report, I have shown that the enacted plan unduly favors the Republican Party. In this section, I will examine whether it favors incumbents from the Republican Party. I find that it does.

In order to examine whether the new plan favors incumbents from the Republican Party, I first examine the percentage of the Democratic and Republican voters in each

30. Note that the margins here are based on the unrounded vote shares in each district. Also, according to PlanScore, Republicans have at least a 64% chance of winning each of these districts.

2020 Districts	2022 District	% Overlap	Dem. Vote Share Old District	Dem. Vote Share New District
1	1	0.81	0.46	0.48
2	2	0.68	0.39	0.29
3	3	0.71	0.71	0.70
4	4	0.53	0.30	0.30
5	9	0.56	0.32	0.46
6	6	0.61	0.26	0.38
7	7	0.41	0.30	0.37
8	8	0.80	0.31	0.36
9	9	0.44	0.63	0.46
10	10	0.97	0.42	0.42
11	11	0.79	0.80	0.79
12	4	0.41	0.43	0.30
13	6	0.54	0.54	0.38
14	14	0.73	0.40	0.40
15	15	0.43	0.37	0.43
16	13	0.48	0.37	0.47

Table 9: Evaluation of how incumbent in each of the old districts would perform on the enacted plan based on re-aggregating the 2020 House results to new districts. Districts won by Democrats in 2020 in blue.

of the 16 districts used in the 2020 congressional election that will be in each of the 15 districts on the enacted plan. This enables me to determine the new district that most overlaps with each of the old districts. I then compare the incumbent's vote share in each district of the old plan to their expected vote share in the new plan by re-aggregating the 2020 House elections to the new district that most overlaps with the old districts.

Table 9 shows the results. It shows that the enacted plan favors incumbents from the Republican Party. It puts the Democratic incumbents in districts 9 and 13 into largely new districts that will now have a majority of Republican voters. Democratic incumbent Tim Ryan in district 13 is retiring and running for Senate, so maybe we should put less weight on this district. But it is very clear that the plan is drawn to harm Representative Marcy Kaptur.

Representative Kaptur's old district 9 went along the Lake Erie coastline from Toledo to the Cleveland suburbs. In 2020, she comfortably won reelection with 63% of the two-party vote on the 2020 map. Her new district, however, goes from the Indiana border to a bit west of Lorain. It no longer includes any of the Democratic-leaning Cleveland suburbs. Overall, the new district 9 only includes 44% of the voters from Kaptur's old district 9. On the new map, she would have only won about 46% in the 2020 House election, and thus would likely lose in 2022.

7 Conclusion

Overall, there is a substantial Republican bias in the translation of votes to seats in the enacted congressional plan in Ohio. Based on a variety of metrics, the pro-Republican bias in Ohio's congressional districting plan is very large relative to other states over the past 50 years. Moreover, the new map does not contain significantly more competitive districts than the 2012-2020 plan. The plan unduly favors congressional candidates from the Republican Party.

ADAMS_00049

References

Best, Robin E, Shawn J Donahue, Jonathan Krasno, Daniel B Magleby, and Michael D McDonald. 2017. "Considering the Prospects for Establishing a Packing Gerrymandering Standard." *Election Law Journal: Rules, Politics, and Policy.*

Brace, Kimball, Bernard Grofman, and Lisa Handley. 1987. "Does Redistricting Aimed to Help Blacks Necessarily Help Republicans?" *Journal of Politics* 49 (1): 169–185.

Brennan Center. 2017. *Extreme Maps.* `https://www.brennancenter.org/publication/extreme-maps`.

Buzas, Jeffrey S, and Gregory S Warrington. 2021. "Simulated packing and cracking." *Election Law Journal: Rules, Politics, and Policy.*

Caughey, Devin, Chris Tausanovitch, and Christopher Warshaw. 2017. "Partisan Gerrymandering and the Political Process: Effects on Roll-Call Voting and State Policies." *Election Law Journal* 16 (4).

Chen, Jowei, and Jonathan Rodden. 2013. "Unintentional Gerrymandering: Political Geography and Electoral Bias in Legislatures." *Quarterly Journal of Political Science* 8 (3): 239–269.

Cox, Gary W., and Jonathan N. Katz. 1999. "The reapportionment revolution and bias in US congressional elections." *American Journal of Political Science:* 812–841.

———. 2002. *Elbridge Gerry's Salamander: The Electoral Consequences of the Reapportionment Revolution.* New York: Cambridge University Press.

Fraga, Bernard L, and Eitan D Hersh. 2018. "Are Americans stuck in uncompetitive enclaves? An appraisal of US electoral competition." *Quarterly Journal of Political Science* 13 (3): 291–311.

Gelman, Andrew, and Gary King. 1994a. "A unified method of evaluating electoral systems and redistricting plans." *American Journal of Political Science* 38 (2): 514–554.

———. 1994b. "Enhancing Democracy Through Legislative Redistricting." *American Political Science Review* 88 (03): 541–559.

Henderson, John A, Brian T Hamel, and Aaron M Goldzimer. 2018. "Gerrymandering Incumbency: Does Nonpartisan Redistricting Increase Electoral Competition?" *The Journal of Politics* 80 (3): 1011–1016.

ADAMS_00050

Jacobson, Gary C. 2015. "It's nothing personal: The decline of the incumbency advantage in US House elections." *The Journal of Politics* 77 (3): 861–873.

———. 2021. "The presidential and congressional elections of 2020: A national referendum on the Trump presidency." *Political Science Quarterly (Wiley-Blackwell):* 11–45.

Jacobson, Gary C, and Jamie L Carson. 2015. *The politics of congressional elections.* Rowman & Littlefield.

Katz, Jonathan N, Gary King, and Elizabeth Rosenblatt. 2020. "Theoretical foundations and empirical evaluations of partisan fairness in district-based democracies." *American Political Science Review* 114 (1): 164–178.

Kollman, K., A. Hicken, D. Caramani, D. Backer, and D. Lublin. 2017. *Constituency-level elections archive [data file and codebook].* Ann Arbor, MI: Center for Political Studies, University of Michigan.

Krasno, Jonathan S, Daniel Magleby, Michael D McDonald, Shawn Donahue, and Robin E Best. 2018. "Can Gerrymanders Be Detected? An Examination of Wisconsin's State Assembly." *American Politics Research.*

McGhee, Eric. 2014. "Measuring Partisan Bias in Single-Member District Electoral Systems." *Legislative Studies Quarterly* 39 (1): 55–85.

———. 2017. "Measuring Efficiency in Redistricting." *Election Law Journal: Rules, Politics, and Policy.*

———. 2018. *Assessing California's Redistricting Commission: Effects on Partisan Fairness and Competitiveness.* Report from the Public Policy Institute of California. Available at `http://www.ppic.org/publication/assessing-californias-redistricting-commission-effects-on-partisan-fairness-and-competitiveness/`.

MIT Election and Data Science Lab. 2017. *U.S. House 1976–2016.* Available on the Harvard Dataverse at `http://dx.doi.org/10.7910/DVN/IG0UN2`.

Nagle, John F. 2015. "Measures of partisan bias for legislating fair elections." *Election Law Journal* 14 (4): 346–360.

Niemi, Richard G, and John Deegan. 1978. "A theory of political districting." *American Political Science Review* 72 (4): 1304–1323.

ADAMS_00051

Powell, G. Bingham, Jr. 2004. "Political Representation in Comparative Politics." *Annual Review of Political Science* 7:273–296.

Royden, Laura, Michael Li, and Yurij Rudensky. 2018. *Extreme Gerrymandering & the 2018 Midterm.*

Stephanopoulos, Nicholas. 2018. "The Causes and Consequences of Gerrymandering." *William and Mary Law Review* 59.

Stephanopoulos, Nicholas O, and Christopher Warshaw. 2020. "The impact of partisan gerrymandering on political parties." *Legislative Studies Quarterly* 45 (4): 609–643.

Stephanopoulos, Nicholas O., and Eric M. McGhee. 2015. "Partisan Gerrymandering and the Efficiency Gap." *University of Chicago Law Review* 82 (2): 831–900.

———. 2018. "The measure of a metric: The debate over quantifying partisan gerrymandering." *Stan. L. Rev.* 70:1503.

Tufte, Edward R. 1973. "The relationship between seats and votes in two-party systems." *American Political Science Review* 67 (2): 540–554.

Wang, Samuel. 2016. "Three Tests for Practical Evaluation of Partisan Gerrymandering." *Stan. L. Rev.* 68:1263–1597.

Warrington, Gregory S. 2018a. "Introduction to the declination function for gerrymanders." *arXiv preprint arXiv:1803.04799.*

———. 2018b. "Quantifying Gerrymandering Using the Vote Distribution." *Election Law Journal* 17 (1): 39–57.

ADAMS_00052

Supplementary Appendix

A Alternative Composite Indices

Metric	Value	More Biased than this % Historical Plans	More Pro-Republican than this % Historical Plans
2012-2020 Plan			
Efficiency Gap	-13%	86%	94%
Declination	-.47	83%	89%
Mean-Median Diff	-3%	45%	73%
Symmetry	-19%	93%	94%
Average		77%	88%
Enacted Plan			
Efficiency Gap	-10%	75%	89%
Declination	-.38	78%	85%
Mean-Median Diff	-2%	24%	63%
Symmetry	-14%	84%	90%
Average		65%	82%

Table A1: Composite partisan bias metrics for Congressional plan based on federal statewide elections from 2012-2020

Metric	Value	More Biased than this % Historical Plans	More Pro-Republican than this % Historical Plans
2012-2020 Plan			
Efficiency Gap	-10%	74%	89%
Declination	-.41	79%	86%
Mean-Median Diff	-3%	39%	71%
Symmetry	-17%	91%	93%
Average		77%	88%
Enacted Plan			
Efficiency Gap	-11%	79%	91%
Declination	-.44	81%	88%
Mean-Median Diff	-1%	19%	61%
Symmetry	-13%	82%	88%
Average		70%	85%

Table A2: Composite partisan bias metrics for Congressional plan based on all federal elections from 2016-2020

Metric	Value	More Biased than this % Historical Plans	More Pro-Republican than this % Historical Plans
2012-2020 Plan			
Efficiency Gap	-16%	90%	96%
Declination	-.56	89%	93%
Mean-Median Diff	-3%	39%	71%
Symmetry Bias	-17%	91%	93%
Average		77%	88%
Enacted Plan			
Efficiency Gap	-18%	93%	97%
Declination	-.59	92%	95%
Mean-Median Diff	-2%	24%	63%
Symmetry Bias	-10%	69%	83%
Average		70%	85%

Table A3: Composite partisan bias metrics for Congressional plan based on all 2016-2020 statewide elections

Imai Affidavit.pdf

DocVerify ID:	D8970D65-ECBB-4BFE-B639-1BE659039744
Created:	December 09, 2021 07:57:36 -8:00
Pages:	1
Remote Notary:	Yes / State: OH

This document is a DocVerify VeriVaulted protected version of the document named above. It was created by a notary or on the behalf of a notary, and it is also a DocVerify E-Sign document, which means this document was created for the purposes of Electronic Signatures and/or Electronic Notary. Tampered or altered documents can be easily verified and validated with the DocVerify veriCheck system. This remote online notarization involved the use of communication technology.

Go to www.docverify.com at any time to verify or validate the authenticity and integrity of this or any other DocVerify VeriVaulted document.

E-Signature Summary

E-Signature 1: Kosuke Imai (KI)
December 09, 2021 08:01:53 -8:00 [9DB37A030428] [108.26.227.252]
imai@harvard.edu (Principal) (Personally Known)

E-Signature Notary: Theresa M Sabo (TMS)
December 09, 2021 08:01:53 -8:00 [C9A5EA4809AA] [74.142.214.254]
tess.sabo@gmail.com
I, Theresa M Sabo, did witness the participants named above electronically sign this document.

DocVerify documents cannot be altered or tampered with in any way once they are protected by the DocVerify VeriVault System. Best viewed with Adobe Reader or Adobe Acrobat. All visible electronic signatures contained in this document are symbolic representations of the persons signature, and not intended to be an accurate depiction of the persons actual signature as defined by various Acts and/or Laws.

IN THE SUPREME COURT OF OHIO

LEAGUE OF WOMEN VOTERS OF OHIO, *et al.*,

Relators,

v.

OHIO REDISTRICTING COMMISSION, *et al.*,

Respondents.

Case No. 2021-1449

Original Action Filed Pursuant to Ohio Const., Art. XIX, Sec. 1(C)(3)

AFFIDAVIT OF KOSUKE IMAI

Franklin County
/ss
State of Ohio

Now comes affiant Kosuke Imai, having been first duly cautioned and sworn, deposes and states as follows:

1. I am over the age of 18 and fully competent to make this declaration. I have personal knowledge of the statements and facts contained herein.
2. For the purposes of this litigation, I have been asked by counsel for Relators to analyze relevant data and provide my expert opinions.
3. To that end, I have personally prepared the report attached to this affidavit as Exhibit A, and swear to its authenticity and to the faithfulness of the opinions expressed, and, to the best of my knowledge, the accuracy of the factual statements made therein.

FURTHER AFFIANT SAYETH NAUGHT

Executed on 12/09/2021, 2021.

Kosuke Imai
Signed on 2021/12/09 08:01:53 -8:00

Kosuke Imai

Sworn and subscribed before me this 12/09/2021 day of ________, 2021

Signed on 2021/12/09 08:01:53 -8:00

Notary Public

NOTARY PUBLIC
STATE OF OHIO
Theresa M Sabo
Commission # 2016-RE-619622
Electronic Notary Public
State of Ohio
My Comm Exp. Nov 28, 2026
Notary Stamp 2021/12/09 09:01:53 PST C9A5EA4809AA

Notarial act performed by audio-visual communication

ADAMS_00056

D8970D65-ECBB-4BFE-B639-1BE659039744 --- 2021/12/09 07:57:36 -8:00 --- Remote Notary

EXHIBIT A

IN THE SUPREME COURT OF OHIO

League of Women Voters of Ohio, *et al.* *Relators*, v. Ohio Redistricting Commission, *et al.* *Respondents*.	Original Action Filed Pursuant to Ohio Const., Art. XIX, Sec. 3(A)

EXPERT REPORT
Kosuke Imai, Ph.D.
December 9, 2021

Table of Contents

I. INTRODUCTION AND SCOPE OF WORK

1. My name is Kosuke Imai, Ph.D., and I am a Professor in the Department of Government and the Department of Statistics at Harvard University. I specialize in the development of statistical methods for and their applications to social science research. I am also affiliated with Harvard's Institute for Quantitative Social Science.

2. I have been asked by counsel representing the relators in this case to analyze relevant data and provide my expert opinions related to whether Ohio's enacted congressional districting plan (SB 258, which I will refer to as the "enacted plan" in this report) meets the criteria in Article XIX, Section 1(C)(3)(a) of Ohio's Constitution. More specifically, I have been asked to statistically analyze the enacted plan's compliance with Article XIX, Section 1(C)(3)(a)'s requirement that "[t]he general assembly shall not pass a plan that unduly favors or disfavors a political party or its incumbents" by comparing it against other alternative plans that are as or more compliant with other relevant requirements of Article XIX.

II. SUMMARY OF OPINIONS

3. I simulated 5,000 hypothetical plans that are at least as compliant with Article XIX as the enacted plan. The comparison of these simulated plans with the enacted plan yields the following findings:

- The enacted plan unduly favors the Republican Party by giving the Republicans a much greater expected number of seats than in any of my 5,000 simulated plans. Even using the General Assembly's assumptions regarding the appropriate election set and calculation of expected number of seats, the Republican candidates are expected to win 2.8 more seats under the enacted plan than under the average simulated plan.

- The expected number of Republican seats under the enacted plan is a clear statistical outlier. Indeed, any plan that provides for more than 9 expected Republican seats is an outlier. Moreover, the probability of generating the enacted plan's extreme partisan outcome under the non-partisan simulation procedure I used is essentially zero.

- The enacted plan exhibits a significant partisan bias in favor of the Republican Party. Even using the General Assembly's assumptions regarding the appropriate election set and calculation of expected number of seats, the magnitude of bias is much greater under the enacted plan than in any of my 5,000 simulated plans and is a clear statistical outlier, according to several standard metrics used in the academic literature.
- In Hamilton County, the enacted plan cracks Democratic voters to create safe Republican seats, while in Franklin and Cuyahoga counties the enacted plan packs Democratic voters to create additional Republican-leaning districts.

III. QUALIFICATIONS, EXPERIENCE, AND COMPENSATION

4. I am trained as a political scientist (Ph.D. in 2003, Harvard) and a statistician (MA in 2002, Harvard). I have published more than 60 articles in peer reviewed journals, including premier political science journals (e.g., *American Journal of Political Science*, *American Political Science Review*, *Political Science*), statistics journals (e.g., *Biometrika*, *Journal of the American Statistical Association*, *Journal of the Royal Statistical Society*), and general science journals (e.g., *Lancet*, *Nature Human Behavior*, *Science Advances*). My work has been widely cited across a diverse set of disciplines. For each of the past four years, Clarivate Analytics, which tracks citation counts in academic journals, has named me as a highly cited researcher in the cross-field category for producing "multiple highly cited papers that rank in the top 1% by citations for field and year in Web of Science."

5. I started my academic career at Princeton University, where I played a leading role in building interdisciplinary data science communities and programs on campus. I was the founding director of Princeton's Program in Statistics and Machine Learning from 2013 to 2017. In 2018, I moved to Harvard, where I am Professor jointly appointed in the Department of Government and the Department of Statistics, the first such appointment in the history of the university. Outside of universities, between 2017 and 2019, I served as the president of the Society for Political Methodology, a primary academic organization of more than one thousand researchers worldwide who conduct methodological research in political science. My introductory statistics textbook for

social scientists, *Quantitative Social Science: An Introduction* (Princeton University Press, 2017), has been widely adopted at major research universities in the United States and beyond.

6. Computational social science is one of my major research areas. As part of this research agenda, I have developed simulation algorithms for evaluating legislative redistricting since the beginning of this emerging literature. At Harvard, I lead the Algorithm-Assisted Redistricting Methodology (ALARM; https://alarm-redist.github.io/) Project, which studies how algorithms can be used to improve legislative redistricting practice and evaluation.

7. Back in 2014, along with Jonathan Mattingly's team at Duke, my collaborators and I were the first to use Monte Carlo algorithms to generate an ensemble of redistricting plans. Since then, my team has written several methodological articles on redistricting simulation algorithms (Fifield, Higgins, et al. 2020; Fifield, Imai, et al. 2020; McCartan and Imai 2020; Kenny et al. 2021).

8. I have also developed an open-source software package titled `redist` that allows researchers and policy makers to implement the cutting-edge simulation methods developed by us and others (Kenny et al. 2020). This software package can be installed for free on any personal computer with Windows, Mac, or Linux operating system. According to a website that tracks the download statistics of R packages, our software package has been downloaded about 30,000 times since 2016 with an increasing download rate.[1]

9. In addition to redistricting simulation methods, I have also developed the methodology for ecological inference referenced in voting rights cases (Imai, Lu, and Strauss 2008; Imai and Khanna 2016). For example, my methodology for predicting individual's race using voter files and census data was extensively used in a recent decision by the Second Circuit Court of Appeals regarding a redistricting case (Docket No. 20-1668; Clerveaux *et al* v. East Ramapo Central School District).

10. A copy of my curriculum vitae is attached as Exhibit A.

11. I am being compensated at a rate of $450 per hour. My compensation does not

1. https://ipub.com/dev-corner/apps/r-package-downloads/ (accessed on December 6, 2021)

depend in any way on the outcome of the case or on the opinions and testimony that I provide.

IV. METHODOLOGY

12. I conducted simulation analyses to evaluate the enacted plan's compliance with Section 1(C)(3)(a) of Article XIX. Redistricting simulation algorithms generate a representative sample of all possible plans under a specified set of criteria. This allows one to evaluate the properties of a proposed plan by comparing them against those of the simulated plans. If the proposed plan unusually favors one party over another *when compared to* the ensemble of simulated plans, this serves as empirical evidence that the proposed plan is a partisan gerrymander. Furthermore, statistical theory allows us to quantify the degree to which the proposed plan is extreme relative to the ensemble of simulated plans in terms of partisan outcomes.

13. A primary advantage of the simulation-based approach, over the traditional methods, is its ability to account for the political and geographic features that are specific to each state, including spatial distribution of voters and configuration of administrative boundaries. Simulation methods can also incorporate each state's redistricting rules. These state-specific features limit the types of redistricting plans that can be drawn, making comparison across states difficult. The simulation-based approach therefore allows us to compare the enacted plan to a representative set of alternate districting plans subject to Ohio's administrative boundaries, political realities, and constitutional requirements. Appendix A provides a brief introduction to redistricting simulation.

A. Simulation Analysis

14. I have ensured that all my simulated plans are equally or more compliant with Section 2(B) of Article XIX than the enacted plan. My simulation procedure achieves this, in part, by being compliant with the U.S. Constitution and federal law protecting racial minority voting rights, generating contiguous and compact districts, limiting the number of county splits, and respecting the other splitting criteria specified in Section 2(B). I also avoid splitting the counties the enacted plan does not split. Appendix B provides detailed information about this process. For all simulations, I ensure districts fall within a 0.5% deviation from population parity. Although this deviation is greater than the population deviation used in the enacted plan, it only accounts for less

than 4,000 people and hence has no impact on the conclusions of my analysis.

15. Here, I provide a brief overview of the procedure while leaving the details to Appendix B. My simulation proceeds in two steps. First, at the instruction of counsel for the relators, I ensured that every simulated plan has one district in Cuyahoga County with the proportion of black voting age population (BVAP) falling above 42% in order to be compliant with the U.S. Constitution and federal law protecting racial minority voting rights. To do this, I sampled a contiguous and compact district that has an appropriate population size and BVAP proportion within Cuyahoga County. This district always contains the entire city of Cleveland because Section 2(B)(4)(b) prohibits splitting it. Once such a district is generated, I then separately run the simulation algorithm on the rest of the state and generate the remaining 14 districts while making sure that the resulting districts satisfy the requirements specified in Section 2(B). I repeat this procedure 5,000 times to obtain the desired number of simulated plans.

B. Metrics Used to Measure Bias

16. Using the redistricting simulation methodology, I evaluate compliance with Section 1(C)(3)(a) of Article XIX in the set of simulated plans generated by the algorithm as well as the enacted plan. To determine whether the enacted plan unduly favors a particular political party, I compare the expected number of Republican and Democratic seats under the enacted plan against the corresponding number under the simulated plans.

17. I understand that the General Assembly assessed the partisan leanings of the enacted plan using the set of six statewide federal elections from 2012 to 2020 (see Appendix E.1 for the list of these elections). I do not endorse the assumption that using this limited data set can accurately predict the expected number of Republican and Democratic seats under the enacted plan.[2] I nonetheless use this same set of election results data in my analysis so that the differences in conclusions between my analysis and the General Assembly's assessment cannot be attributed to the way in which the partisan leanings of districts are evaluated. Given that these elections

2. I have reviewed the Affidavit of Dr. Christopher Warshaw dated November 30, 2021, which concludes that this set of elections artificially enhances the perception of Democratic Party strength under the enacted plan. I agree with his conclusion in this regard.

enhance the perception of Democratic relative strength, using this assumption effectively gives the enacted plan the benefit of the doubt.

18. I also adopt the General Assembly's approach to computing the expected number of Republican seats under a given redistricting plan. Specifically, I first compute the total number of Republican votes for each district and then sum it across the six statewide federal elections. Dividing this by the total number of two-party votes that are similarly aggregated across these elections yields the Republican two-party vote share for each district. This aggregation method may not be ideal because it gives greater weights to general elections, which tend to have higher turnout than midterm elections. In spite of this potential problem, I follow the General Assembly's approach so that the findings of my analysis can be directly compared to the General Assembly's assessment. I have confirmed that the resulting vote share for each district under the enacted plan is essentially identical to the corresponding district-level vote share presented in the November 16, 2021 statement from Senator Rob McColley. Finally, based on these vote shares, I determine likely winners of all districts based on the vote totals for each statewide election. This gives the total number of expected Republican and Democratic seats for a given plan under the General Assembly's approach.

19. In addition to the expected number of seats, I apply a variety of metrics that are commonly used in the academic literature. These metrics are extensively discussed in Dr. Christopher Warshaw's affidavit, dated November 30, 2021, and the references therein. I have reviewed Dr. Warshaw's articulation of these metrics and they are consistent with my understanding, and appear to be applicable to the facts of this case. Specifically, to measure compliance with Section 1(C)(3)(a), I use the following partisan bias metrics whose definitions are discussed in Dr. Warshaw's affidavit and the references therein.

- Efficiency gap
- Mean-median gap
- Symmetry in the vote-seat curve across parties
- Declination

C. The Determination of Whether the Enacted Plan is a Statistical Outlier Can Provide a Useful Measure of its Partisan Bias

20. Another important benefit of using the redistricting simulation methodology is that it can determine whether or not the enacted plan is a statistical outlier relative to the simulated plans generated under a specified set of criteria. If the enacted plan is a statistical outlier, then the observed difference in partisan outcome between the enacted plan and the simulated plans represents a systematic partisan bias.

21. To determine whether the enacted plan is a statistical outlier, I first estimate the probability of generating a simulated plan that favors a political party at least as much as the enacted plan does. This can be done by simply computing the proportion of the simulated plans that favors a political party equally or more than the enacted plan. If this estimated probability is very small (e.g., less than 0.001), then the enacted plan is a statistical outlier because it is highly unlikely to come from the non-partisan distribution that is used to generate the simulated plans. If the data based on the simulated plans follow the normal distribution, which is a bell-shaped symmetric distribution without skew, then this probability of 0.001, for example, implies that the enacted plan is more than three standard deviations away from the average simulated plans.[3]

22. I also compute the difference in partisan outcome between the enacted plan and the average simulated plan. This allows me to measure the magnitude of partisan bias while accounting for its random variability across the simulated plans. I apply the most commonly used definition of an outlier (Tukey 1977). According to this definition, an outlier represents a data point that is beyond a distance of 1.5 interquartile range (IQR) below the first quartile or above the third quartile. If the data based on the simulated plans were normally distributed, the enacted plan is regarded as an outlier if it is at least 2.70 standard deviations away from the average simulated plan.

D. Description of Redistricting Simulation Software

3. Note that a standard deviation represents the average distance between a data point and the mean.

23. In my analysis, I use the open-source software package for redistricting analysis `redist` (Kenny et al. 2020), which implements a variety of redistricting simulation algorithms as well as other evaluation methods. My collaborators and I have written the code for this software package, so that other researchers and the general public can implement these state-of-the-art methods on their own. I supplement this package with code written primarily to account for the redistricting rules and criteria that are specific to Ohio. All of my analyses are conducted on a laptop. Indeed, all of my analysis code can be run on any personal computer once the required software packages, which are also freely available and open-source, are installed.

V. EVALUATION OF THE ENACTED PLAN USING THE GENERAL ASSEMBLY'S APPROACH

24. Using the redistricting simulation methodology, I evaluate the enacted plan's compliance with Section 1(C)(3)(a). Appendix E.1 provides the detailed information about data sources. I simulated 5,000 alternative Congressional redistricting plans, using the simulation procedure described in Section IV. As explained in Appendix B, every simulated plan is at least as compliant with Sections 2(B) as the enacted plan. For example, Appendices C and D show that the simulated plans are more compact and have fewer county splits than the enacted plan.

25. I can easily generate additional compliant plans by running the algorithm longer, but for the purpose of my analysis, 5,000 simulated plans will yield statistically precise conclusions. In other words, generating more than 5,000 plans, while possible, will not materially affect the conclusions of my analysis.

26. To evaluate the enacted plan's compliance with Section 1(C)(3)(a), I first compare the expected number of Republican seats under the enacted plan with that under each of my 5,000 simulated plans. Figure 1 shows that under the enacted plan, the Republican Party is expected to win 11 seats.[4] In contrast, under about 80% of the simulated plans, the expected number of Republican seats is only 8, while the Republican Party is expected to win 9 seats under the remaining

4. This prediction of 11 expected seats is based on using the set of six statewide federal elections from 2012 to 2020 that the General Assembly used. Again, I do not endorse the assumption that using this limited data set can accurately predict the expected number of Republican seats.

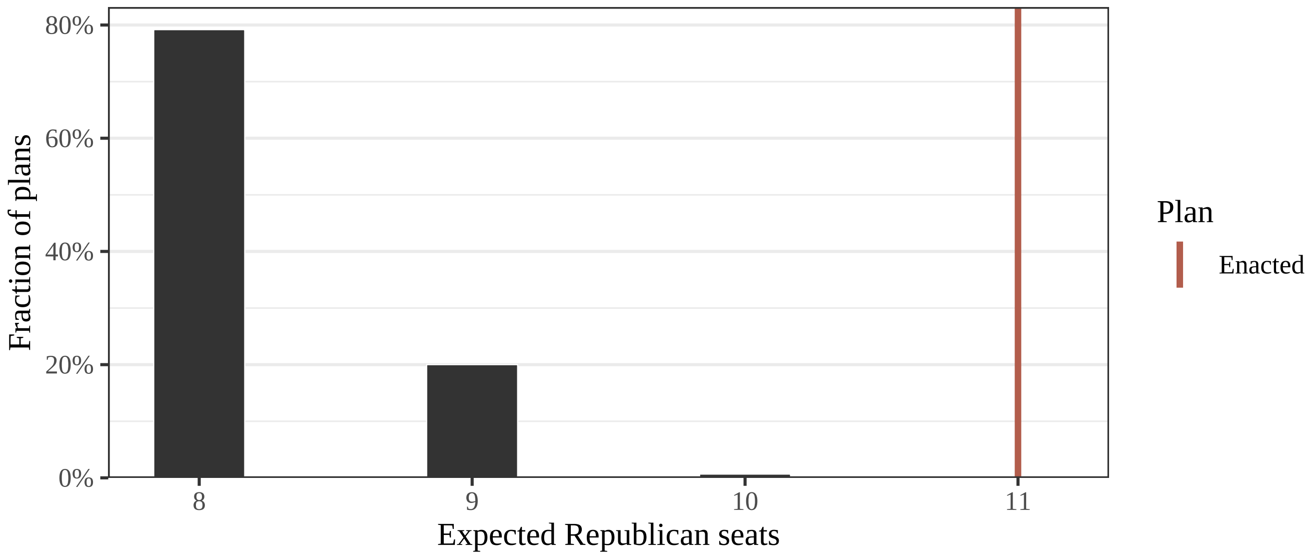

Figure 1: Expected number of Republican seats calculated for the 5,000 simulated plans computed by averaging across the six statewide federal elections from 2012 to 2020. Overlaid is the value for the enacted plan (red).

20% of the simulated plans. In other words, the enacted plan is expected to yield an additional 2.8 Republican seats when compared to the average simulated plan. Indeed, none of my 5,000 simulated plans gives as many Republican seats as the enacted plan. This result implies that the probability of generating the enacted plan's extreme partisan outcome under the non-partisan simulation procedure I used is essentially zero. Thus, any redistricting plan that gives more than 9 seats to the Republican Party, including the enacted plan, is a clear statistical outlier.

27. Under most of the simulated plans, the Republican Party is expected to win 8 seats, which is equivalent to 53% of the Ohio's 15 Congressional seats. This seat proportion is almost identical to the statewide vote share of the Republican Party, which is approximately 52% calculated using the General Assembly's approach and 54% based on the statement made by the Ohio Redistricting Commission in compliance with Section 8(C)(2) of Article XI of the Ohio Constitution. In contrast, under the enacted plan, the expected seat share of the Republican Party is 73%, which is roughly 20 percentage points greater than its expected vote share. As discussed above, this seat share result is a clear statistical outlier. Accordingly, this shows that the enacted plan unduly favors the Republican Party.

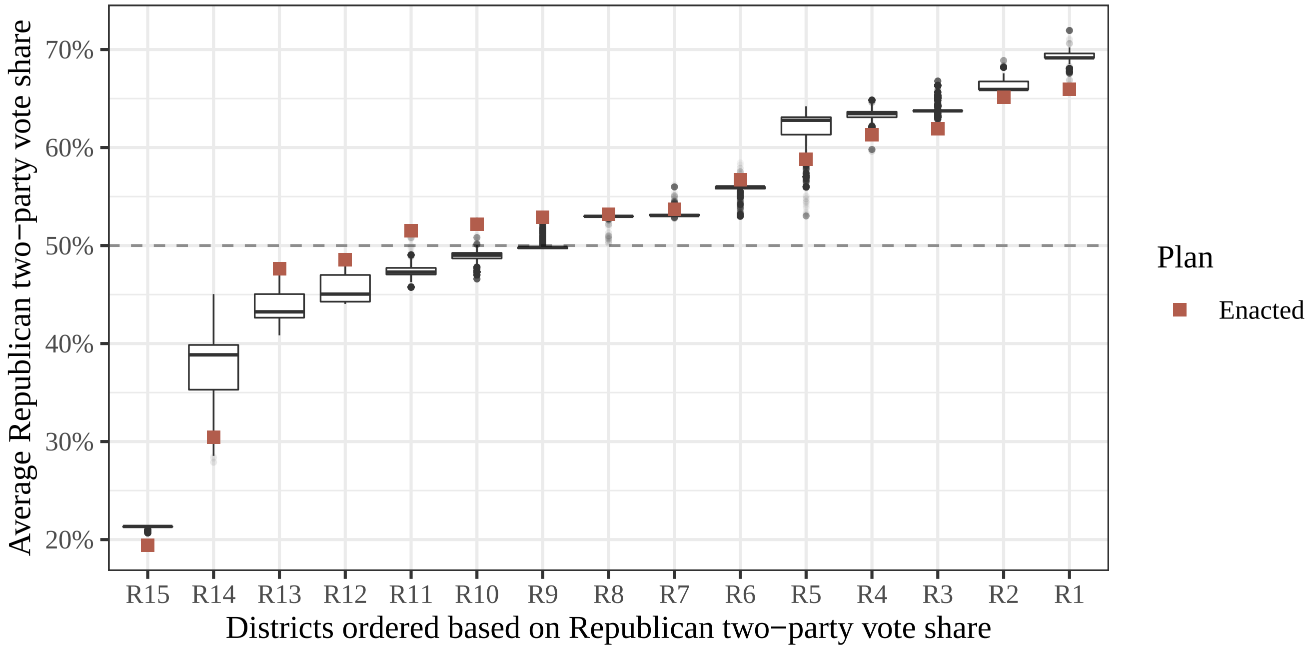

Figure 2: Expected Republican vote share for districts using the six statewide federal elections from 2012 to 2020. For any given plan, the districts are ordered based on their expected Republican vote share. Boxplots represent the distribution of the expected Republican vote share across the simulated plans, whereas the red square correponds to the expected Republican vote share under the enacted plan.

28. Figure 2 further demonstrates the partisan bias of the enacted plan. In this plot, for any given plan (both enacted and simulated), I ordered the districts based on the magnitude of their expected Republican vote share. This means that under any given plan, district R1 yields the highest expected vote share while district R15 is expected to give the least support to the Republican candidate (to be clear, the R1 through R15 district identifiers do not correspond to the Congressional district numbers in the enacted plan). If the expected Republican vote share of each ordered district under the enacted plan (red square) diverges from the corresponding distribution of the simulated plans (boxplot), it constitutes evidence of possible partisan bias. Note that in a boxplot, the "box" contains 50% of the data points (those from 25 percentile to 75 percentile to be exact) with the horizontal line indicating the median value whereas the vertical lines coming out of the box, called "whiskers", indicate the range, which contains most data. Any data points that are beyond these whiskers are considered as outliers according to the second part of the definition

discussed in Section IV.C (paragraph 23).

29. The figure shows clear evidence of the enacted plan's partisan bias. This partisan bias, for the reasons discussed below, further shows that the enacted plan unduly favors the Republican Party. For all of my 5,000 simulated plans, districts R10 and R11 (the 10th and 11th most Republican-leaning districts, respectively) lean toward the Democratic party with the expected median Republican vote share equal to 49.0% and 47.3%, respectively. Indeed, for district R11, none of 5,000 simulated plans are expected to yield as many Republican votes as the enacted plan. Yet under the enacted plan, both of these districts have the expected Republican vote shares above 50%. According to the definition discussed in Section IV.C, these two points associated with the enacted plan are clear statistical outliers, with district R10 and R11 5.2 and 5.8 standard deviations away from the median, respectively.

30. I also find that under the enacted plan, districts R12 and R13 lean much less strongly towards the Democratic party than under all of the simulated plans. Lastly, the enacted plan packs Democratic voters in districts R14 and R15, which are two most Democratic-leaning districts. This is indicated by the fact that these districts have much lower levels of expected Republican vote shares under the enacted plan than under the simulated plans. In contrast, the enacted plan avoids packing Republican voters in the five most Republican districts (districts R1 to R5). Indeed, these districts have much lower levels of expected Republican vote shares under the enacted plan than under the simulated plans. Aside from districts R2 and R5, these points are also statistical outliers. Districts R1 to R5 are 6.8, 1.4, 2.4, 3.7 and 2.0 standard deviations away from the median, respectively.

31. I next use the four partisan bias metrics discussed in Section IV.B to examine the enacted plan's compliance with Section 1(C)(3)(a). I adjusted the sign of each metric so that positive values indicate Republican bias, and values nearer to zero indicate less partisan bias. To summarize the results, as shown in Figure 3, when compared to these simulated plans (black histogram), the enacted plan (red vertical line) is a clear outlier favoring the Republican Party. Indeed, the enacted map is more biased than any of 5,000 simulated plans for all four partisan bias

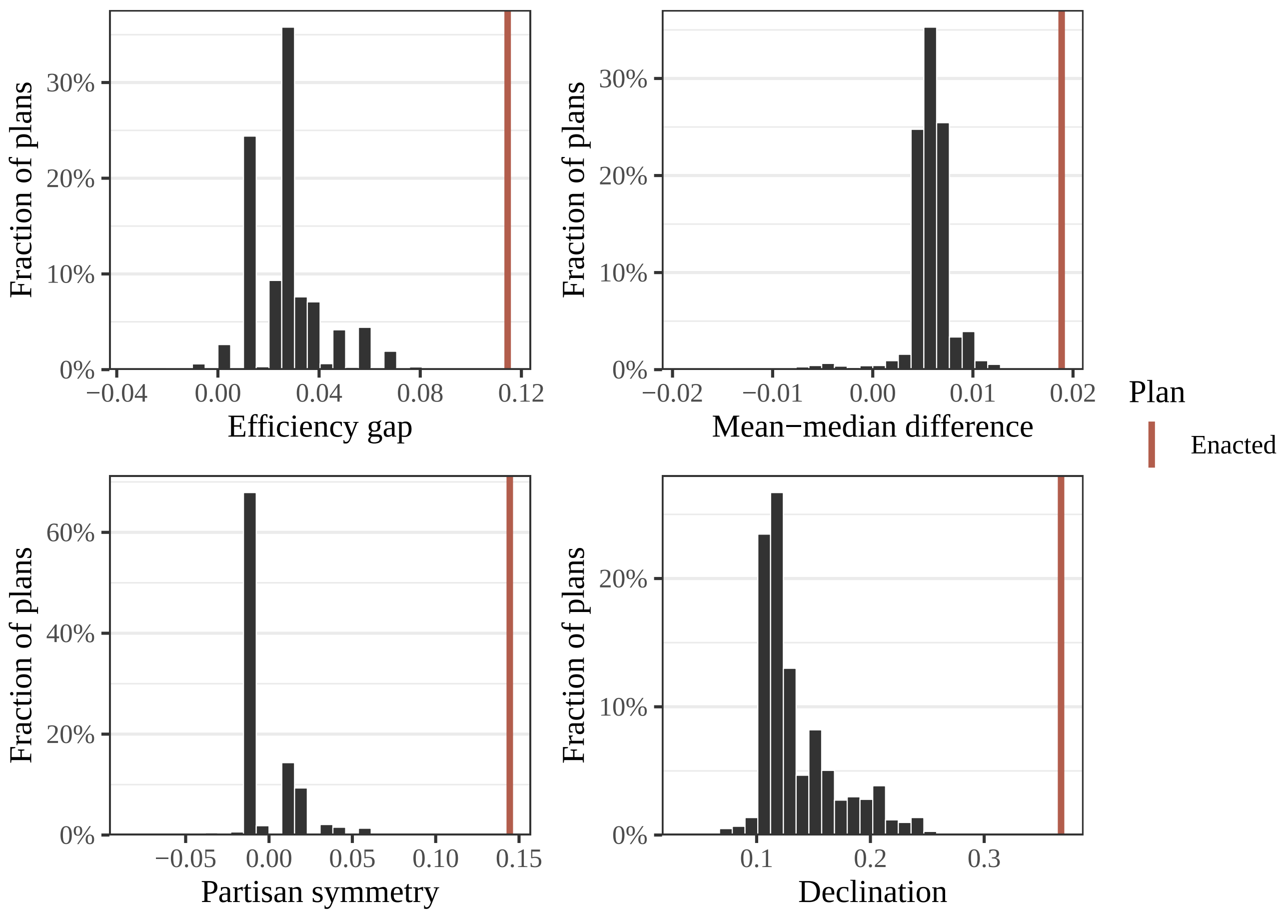

Figure 3: Four partisan bias measures calculated for the 5,000 simulated Congressional redistricting plans computed by averaging across the six federal elections from 2012 to 2020. Overlaid is the value for the enacted plan (red). For each measure, larger values (towards the right) correspond to more Republican-favoring plans.

metrics I considered.

32. The efficiency gap, which captures both cracking and packing, is 15.0% for the enacted map, whereas the average efficiency gap for the simulated plans is only 5.7%. This implies that the enacted plan wastes around 219,000 more Democratic votes on average than the simulated plans, and around 219,000 fewer Republican votes. As shown in the top-left plot of Figure 3, the enacted map is 7.5 standard deviations away from the average simulated plan, and is thus a clear statistical outlier in terms of the efficiency gap metric.

33. The mean-median gap is a measure of asymmetry in the distribution of votes across districts. The existence of packed districts may lead to a large mean-median gap. The top-right plot of the figure shows that the mean-median gap is 0.018 under the enacted plan while the simulated plans score 0.007 on average. Indeed, the enacted plan is 5.7 standard deviations away from the average simulated plan, and is thus a clear statistical outlier in terms of the mean-median gap metric.

34. Partisan symmetry is based on the idea that each party should receive half of the seats if they each receive 50% of votes. The bottom-left plot of Figure 3 shows that the enacted plan scores 14.1% on this metric while the simulated plans score 1.8%, on average. This suggests that under the enacted plan, the Republican Party would gain roughly 2.1 more seats than the Democrats, for a hypothetical tied election. In contrast, the simulated plans would give only 0.3 more seats to the Republican Party than the Democrats in the same situation. The enacted plan is 7.4 standard deviations away from the average simulated plan, and is thus a clear statistical outlier in terms of the partisan symmetry metric.

35. Lastly, the declination metric represents another measure of asymmetry in the vote distribution. As shown in the bottom-right plot of the figure, the enacted plan also scores worse on this metric than any of the 5,000 simulated plans. Specifically, the enacted plan scores 0.42 whereas the simulated plans earn 0.21 on average. The enacted plan is 9.3 standard deviations away from the average simulated plan, and is thus a clear statistical outlier in terms of the declination metric.

36. Thus, all of the partisan bias metrics show that the enacted plan is a clear statistical

outlier, favoring the Republican Party, when compared to the simulated plans. Indeed, the enacted plan has a worse partisan bias than any of my 5,000 simulated plans.

VI. LOCAL ANALYSIS OF SELECTED COUNTIES

37. Partisan bias in the enacted plan is apparent not just in statewide summary statistics, as shown above, but also at the local level. To illustrate this, I performed a detailed analysis of the Congressional districts in Hamilton, Franklin, and Cuyahoga counties. My analysis of these cities shows that the enacted plan packs a disproportionately large number of Democratic voters into some districts while cracking Democratic voters in other districts to create Republican-leaning seats.

38. My analysis of each county proceeds as follows. For each precinct, I first compute the expected two-party vote share of the district to which the precinct is assigned under the enacted plan. I then perform the same calculation under each simulated plan and average these expected vote shares across all of the simulated plans. Comparison of these two numbers reveals whether the enacted plan assigns a precinct to a district whose political leaning is different from what would be expected under the simulated plans. As in Section V, the results shown below are based on the General Assembly's approach that uses the statewide federal elections from 2012-2020.

A. Hamilton County

39. I begin by illustrating the above calculation through an example. Precinct 061031BEZ of Cincinnati lies within District 1 of the enacted map, which has an expected Republican two-party vote share of 51.53%. However, the same precinct belongs to different districts in most of the simulated maps, each with their own Republican vote share. The average Republican vote share for the districts to which this precinct is assigned across all of the simulated plans is 44.85%, which is 6.68 percentage points lower than under the enacted plan. So, based on the representative set of simulated plans that have less partisan bias, precinct 061031BEZ is assigned to a more Republican-leaning district under the enacted plan than under the average simulation plan.

40. The left map of Figure 4 presents the expected vote shares of districts under the

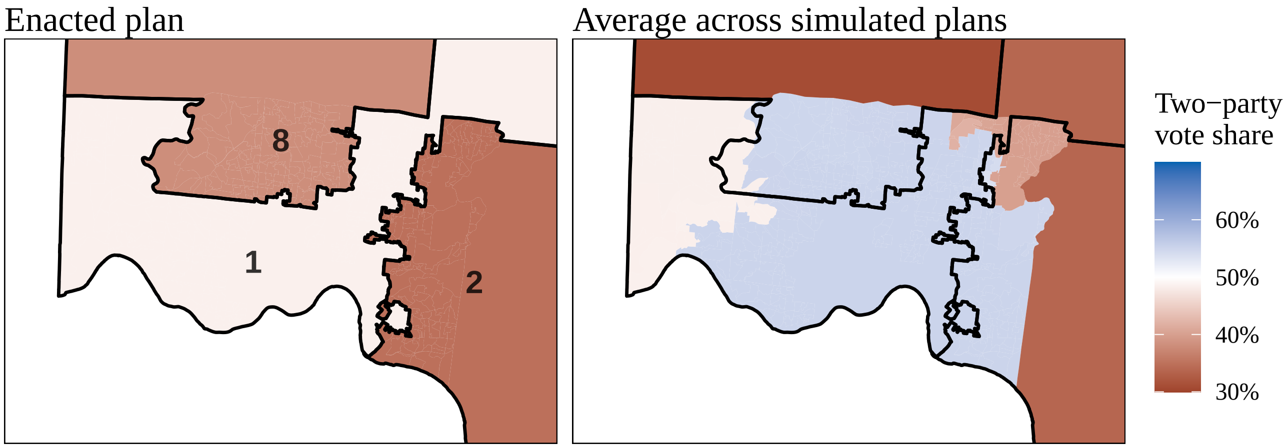

Figure 4: Congressional districts in Hamilton County. The left map presents the expected two-party vote shares of districts under the enacted plan, while the right map shows, for each precinct, the average expected two-party vote share of districts to which the precinct is assigned across the simulated plans. The enacted district boundaries are shown with thick black lines. While under the simulated plans, Cincinnati and its environs are expected to belong to a Democratic-leaning district, the enacted plan cracks Democratic voters, leading to solely Republican districts.

enacted plan, while the right map shows, for each precinct, the average expected two-party vote share of districts to which the precinct is assigned across the simulated plans. Under the enacted plan, Democratic areas are cracked to yield three Republican-leaning districts, despite a significant concentration of Democratic voters in and around Cincinnati. This is especially apparent with the two unusual protrusions of Districts 2 and 8 into Hamilton County, which split the county twice. The simulated plans, in comparison, are expected to only split Hamilton County once. As the right figure indicates, the area covered by these protrusions would normally be expected to belong to a Democratic district, but as a result of being lumped with adjacent districts in the enacted plan, instead belongs to safely Republican districts.

41. As a result of these manipulations and additional splits of Hamilton County, the enacted plan has no Democratic seats under the average statewide federal contest, whereas the simulated plans are expected to yield a Democratic seat. So in Hamilton County alone, cracking of Democratic voters nets Republicans an entire seat.

B. Franklin County

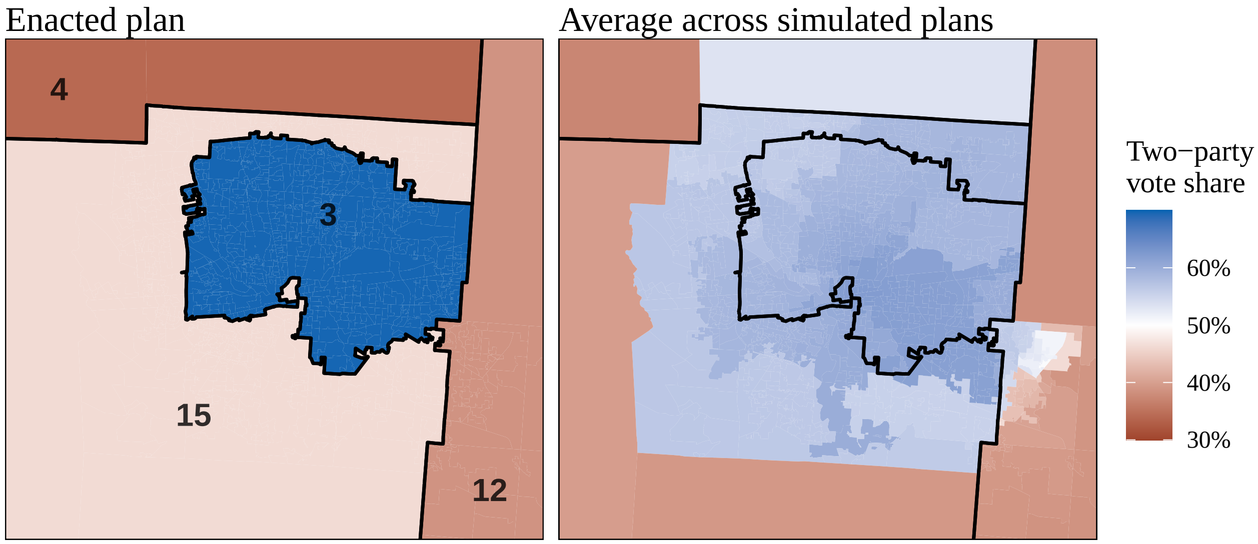

Figure 5: Congressional districts in Franklin County. The left map presents the expected two-party vote shares of districts under the enacted plan, while the right map shows, for each precinct, the average expected two-party vote share of districts to which the precinct is assigned across the simulated plans. The enacted district boundaries are shown with thick black lines. While under the simulated plans, all of Franklin County are expected to belong to a Democratic district, the enacted plan packs Democratic voters, leaving much of the city of Columbus in a Republican district stretching most of the way to Cincinnati.

42. Analogous to Figure 4, Figure 5 compares the enacted plan with the simulated plans in Franklin County. Unlike in Hamilton County, the enacted plan packs Democratic voters into a single, heavily Democratic, District 3, leaving Districts 4, 12, and 15 to be safely Republican. Much of the area inside Franklin County belongs to a safe Republican district under the enacted plan. In contrast, under the simulated plans, the entire area of Franklin County is expected to belong to a Democratic-leaning district, as is Delaware County and part of Fairfield County.

43. By confining Democratic voters to a single district containing part of Columbus, the enacted plan deprives Democratic voters in the rest of the county of a reasonable opportunity to elect a Democratic candidate. In doing so, the enacted plan yields around one additional seat for Republicans, on average, when compared to the simulated plans.

C. Cuyahoga County

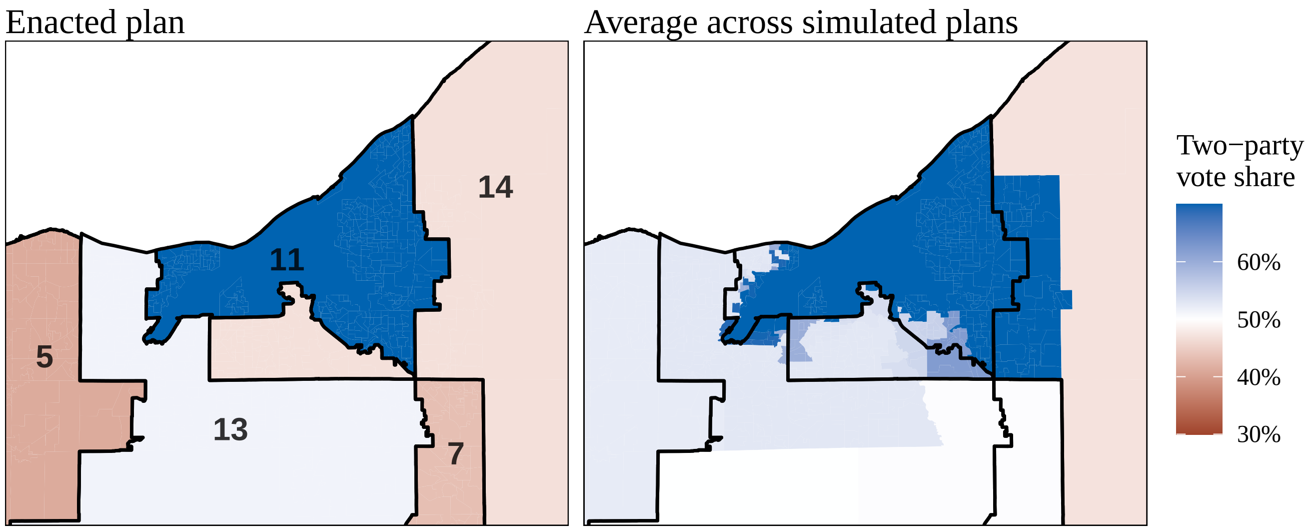

Figure 6: Congressional districts in Cuyahoga County. The left map presents the expected two-party vote shares of districts under the enacted plan, while the right map shows, for each precinct, the average expected two-party vote share of districts to which the precinct is assigned across the simulated plans. The enacted district boundaries are shown with thick black lines. While under the simulated plans, the suburbs of Cleveland are expected to belong to either Democratic districts or highly competitive districts, the enacted plan packs urban Democratic voters, leaving the remainder of Cuyahoga County and nearby areas in Republican districts.

44. Figure 6 is constructed just like Figures 4 and 5. Districts in Cuyahoga County are more constrained than in Franklin County, based on the need to avoid splitting the city of Cleveland, as well as Voting Rights Act considerations. Even so, the enacted plan differs in key ways from the average simulated plan. First, it overly packs Democratic voters in District 11, as indicated by Figure 2 where District 11 corresponds to the least Republican-leaning district (R15). More importantly, Districts 5, 7, 13, and 14 in the enacted plan are drawn to crack the remaining Democratic voters outside of Cleveland and in the cities of Lorain and Akron. The result of this is to create three Republican-leaning districts and only one competitive district. In contrast, under the simulated plans, all of the areas south and west of Cleveland are generally expected to belong to competitive or Democratic-leaning districts.

ADAMS_00076

VII. APPENDIX

A. Introduction to Redistricting Simulation

1. In recent years, redistricting simulation algorithms have played an increasingly important role in court cases involving redistricting plans. Simulation evidence has been presented to courts in many states, including Michigan, North Carolina, Ohio, and Pennsylvania.[5]

2. Over the past several years, researchers have made major scientific advances to improve the theoretical properties and empirical performance of redistricting simulation algorithms. All of the state-of-the-art redistricting simulation algorithms belong to the family of Monte Carlo methods. They are based on random generation of spanning trees, which are mathematical objects in graph theory (DeFord, Duchin, and Solomon 2021). The use of these random spanning trees allows these state-of-the-art algorithms to efficiently sample a representative set of plans (Autry et al. 2020; Carter et al. 2019; McCartan and Imai 2020; Kenny et al. 2021). Algorithms developed earlier, which do not use random spanning trees and instead rely on incremental changes to district boundaries, are often not able to do so.

3. These algorithms are designed to sample plans from a specific probability distribution, which means that every legal redistricting plan has certain odds of being generated. The algorithms put as few restrictions as possible on these odds, except to ensure that, on average, the generated plans meet certain criteria. For example, the probabilities are set so that the generated plans reach a certain level of geographic compactness, on average. Other criteria, based on the state in question, may be fed into the algorithm by the researcher. In other words, this target distribution is based on the weakest assumption about the data under the specified constraints.

4. In addition, the algorithms ensure that all of the sampled plans (a) are geographically contiguous, and (b) have a population which deviates by no more than a specified amount

5. Declaration of Dr. Jonathan C. Mattingly, Common Cause v. Lewis (2019); Testimony of Dr. Jowei Chen, Common Cause v. Lewis (2019); Testimony of Dr. Pegden, Common Cause v. Lewis (2019); Expert Report of Jonathan Mattingly on the North Carolina State Legislature, Rucho v. Common Cause (2019); Expert Report of Jowei Chen, Rucho v. Common Cause (2019); Amicus Brief of Mathematicians, Law Professors, and Students in Support of Appellees and Affirmance, Rucho v. Common Cause (2019); Brief of Amici Curaiae Professors Wesley Pegden, Jonathan Rodden, and Samuel S.-H. Wang in Support of Appellees, Rucho v. Common Cause (2019); Intervenor's Memo, Ohio A. Philip Randolph Inst. et al. v. Larry Householder (2019); Expert Report of Jowei Chen, League of Women Voters of Michigan v. Benson (2019).

from a target population.

5. There are two types of general Monte Carlo algorithms which generate redistricting plans with these guarantees and other properties: sequential Monte Carlo (SMC; Doucet, Freitas, and Gordon 2001) and Markov chain Monte Carlo (MCMC; Gilks, Richardson, and Spiegelhalter 1996) algorithms.

6. The SMC algorithm (McCartan and Imai 2020; Kenny et al. 2021) samples many redistricting plans in parallel, starting from a blank map. First, the algorithm draws a random spanning tree and removes an edge from it, creating a "split" in the map, which forms a new district. This process is repeated until the algorithm generates enough plans with just one district drawn. The algorithm calculates a weight for each plan in a specific way so that the algorithm yields a representative sample from the target probability distribution. Next, the algorithm selects one of the drawn plans at random. Plans with greater weights are more likely to be selected. The algorithm then draws another district using the same splitting procedure and calculates a new weight for each updated plan that comports with the target probability distribution. The whole process of random selection and drawing is repeated again and again, each time drawing one additional district on each plan. Once all districts are drawn, the algorithm yields a sample of maps representative of the target probability distribution.

7. The MCMC algorithms (Autry et al. 2020; Carter et al. 2019) also form districts by drawing a random spanning tree and splitting it. Unlike the SMC algorithm, however, these algorithms do not draw redistricting plans from scratch. Instead, the MCMC algorithms start with an existing plan and modify it, merging a random pair of districts and then splitting them a new way.

8. Diagnostic measures exist for both these algorithms which allow users to make sure the algorithms are functioning correctly and accurately. The original papers for these algorithms referenced above provide more detail on the algorithm specifics, empirical validation of their performance, and the appropriateness of the chosen target distribution.

B. Implementation Details

9. In my analysis, I use the SMC algorithm for several reasons. First, unlike the MCMC algorithms, the SMC algorithm generates nearly independent samples, leading to a diverse set of redistricting plans that satisfy the specified constraints. Second, the SMC algorithm avoids splitting political subdivision boundaries where possible, an important consideration in the case of Ohio. Third, Sections 2(B)(2) and 2(B)(3) require districts to be compact and contiguous, respectively. The SMC algorithm automatically satisfy both of these requirements. Appendix C shows that most of simulated plans generate more compact districts than the enacted plan according to the Polsby-Popper measure, which is a common metric of compactness used in the academic literature.

10. My simulation proceeds in two steps. First, I sample a district in Cuyahoga County using a Voting Rights Act (VRA) constraint to be compliant with Section 2(B)(1). At the instruction of counsel for the relators, I sample one district within Cuyahoga County such that its BVAP proportion falls above 42%. This is done by using the constraint of the form $\sqrt{\max(x_b - B(x_b), 0)}$, where x_b is the share of a district's VAP that is Black, and $B(x_b)$ returns the target BVAP percentages closest to x_b from the set $\{0.02, 0.08, 0.42\}$. This is a common way to formulate the VRA constraint (Herschlag et al. 2020). Note that I also instructed the algorithm to never split the City of Cleveland, in accordance with Section 2(B)(4)(b), and not to split Cuyahoga County three times or more, in accordance with Sections 2(B)(4)(a) and 2(B)(5).

11. Once a district is sampled within Cuyahoga, I generate the remaining 14 districts within the rest of the state without the VRA constraint. In this second step, I incorporate several split constraints. According to Section 2(B)(4)(b), municipalities with population between 100,000 people and the Congressional ratio of represetation, that reside in a county with population greater than the Congressional ratio of representation, should not be split. In addition to the City of Cleveland, this provision also applies to the City of Cincinnati. I instruct the SMC algorithm to never split either of these municipalities.

12. Section 2(B)(5) requires that of Ohio's 88 counties, at least 65 counties should not

be split; no more than 18 counties can be split no more than once; no more than 5 counties can be split no more than twice. I made sure that all of my simulated plans satisfy this requirement by not splitting the counties the enacted plan does not split and imposing a constraint that discourages the algorithm from splitting a county. This is accomplished in two pieces. First, the SMC algorithm, by design, can be instructed to attempt to follow county boundaries where possible by drawing spanning trees within counties and then between them; I use this feature. Additionally, I penalize a district which splits a county twice with a score of 3, and I penalize a district which splits a county three or more times with a score of 100. A penalty of 100 is so severe that any such district is effectively discarded. These parameter values are chosen such that the diversity of the simulated plans is reasonable while minimizing the number of county splits.

13. As shown in Appendix D, all of my simulation plans have fewer county splits than the enacted plan. In addition, while the enacted plan splits Hamilton and Cuyahoga counties twice, only 8 of my 5,000 simulated plans split two counties twice. 35.9% of the simulated plans split only Franklin County twice whereas the remaining simulated plans split no counties twice.

14. Section 2(B)(4)(a) applies to single municipality or township that exceeds the Congressional ratio of representation. The only municipality or township that satisfies this criteria is the City of Columbus. The provision states that the map drawers "shall attempt to include a significant portion of that municipal corporation or township in a single district and may include in that district other municipal corporations or townships that are located in that county and whose residents have similar interests as the residents of the municipal corporation or township that contains a population that exceeds the congressional ratio of representation." To satisfy this requirement, I impose a penalty of 0.5 for each additional district that encompasses any part of the city. This has the effect of ensuring that the city is not split into many different districts. Again, this parameter value is chosen such that the diversity of the simulated plans is reasonable while appropriately discouraging Columbus splits. Like the enacted plan, all of my simulated plans split Columbus into two districts but in different ways.

15. According to Section 2(B)(6), for counties that are split by a congressional district,

the part of the district that falls within county lines must be geographically contiguous within the county. This requirement is mathematically guaranteed by the properties of the SMC algorithm; by drawing spanning trees hierarchically, within and then across counties, it is impossible to split off a district which has two discontiguous pieces inside one county.

16. Section 2(B)(7) requires that two congressional districts can share at most the territory of a single county, excepting counties with population greater than 400,000, where another county can be shared. Like Section 2(B)(6), this requirement is guaranteed by the SMC algorithm: each new district will split at most one county, whereas a 2(B)(7) violation would require two districts to each split the same two counties.

17. Section 2(B)(8) states, "The authority drawing the districts shall attempt to include at least one whole county in each congressional district." This provision does not apply when a district is contained entirely within a county or when in conflict with federal law. This requirement is guaranteed by the enacted plans' choice of counties to split: with the exception of Cuyahoga and Franklin counties, which are each large enough to have a district contained entirely within them, every other split county is surrounded by counties which are not split. Since I do not permit the algorithm to split these surrounding counties, every other district is either contained within a single county or includes the entirety of one of these surrounding counties.

C. Compactness of the Simulated Plans

18. I now show that the simulated plans are more compliant with Section 2(B)(2), which requires districts to be compact, than the enacted plan. I use the Polsby–Popper (Polsby and Popper 1991) and edge-removal (DeFord, Duchin, and Solomon 2021; McCartan and Imai 2020) scores, two commonly-used quantitative measures of district compactness. For the edge-removal compactness, I present the fraction of edge kept so that like the Polsby–Popper score, a greater value implies a higher level of compactness. Figure 7 shows that a vast majority of the simulated plans are more compact than the enacted plan according to the Polsby–Popper score. If I instead use the edge-removal compactness score, all of the simulated plans have superior compactness when compared to the enacted plan. The result clearly implies that it is possible to be compliant

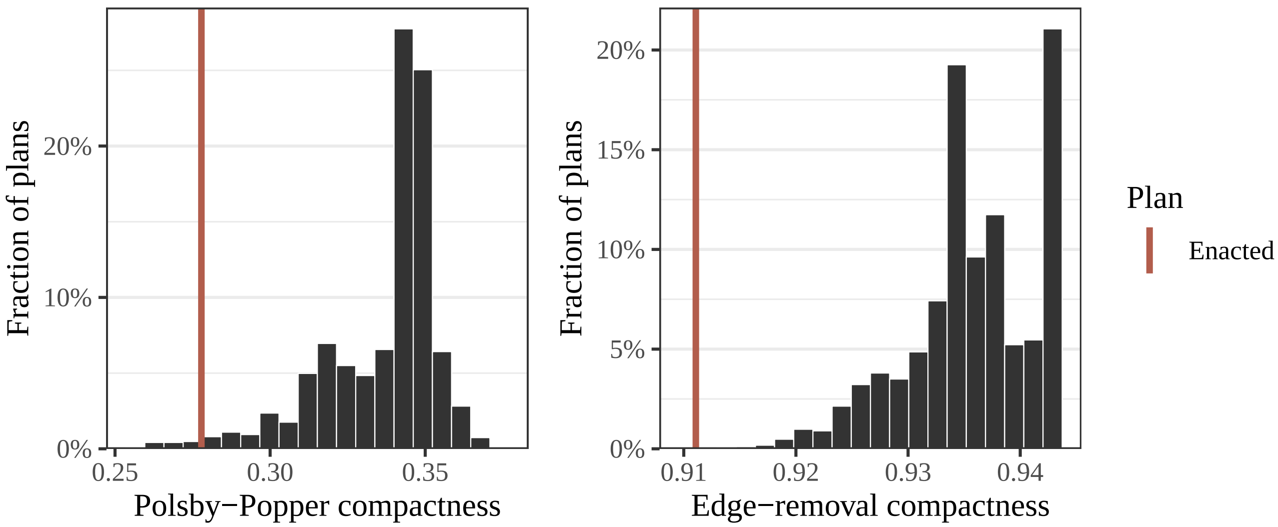

Figure 7: Polsby–Popper and edge–removal compactness scores for the simulated redistricting plans. Overlaid are scores for the enacted plan (red). For both measures, larger values indicate more compact districts.

with Section 1(C)(3)(a) without sacrificing the compliance with Section 2(B)(2).

D. County Splits of the Simulated Plans

19. Similar to compactness, it is possible to be compliant with Section 1(C)(3)(a) without splitting counties more than the enacted plan. The left plot of Figure 8 shows that the number of counties split once is much less under any of the simulated plans than under the enacted plan. The same finding applies to the number of counties that are split twice. As a result, the total number of counties split under the enacted plan is much greater than that under any of the simulated plans.

E. References and Materials Considered

E.1. Data Sources

Data Aquisition

- I analyze a total of 13 statewide elections: US President (2012, 2016, 2020), US Senate (2012, 2016, 2018), Secretary of State (2014, 2018), Governor (2014, 2018), Attorney General (2018), Treasurer (2018), Auditor (2018)

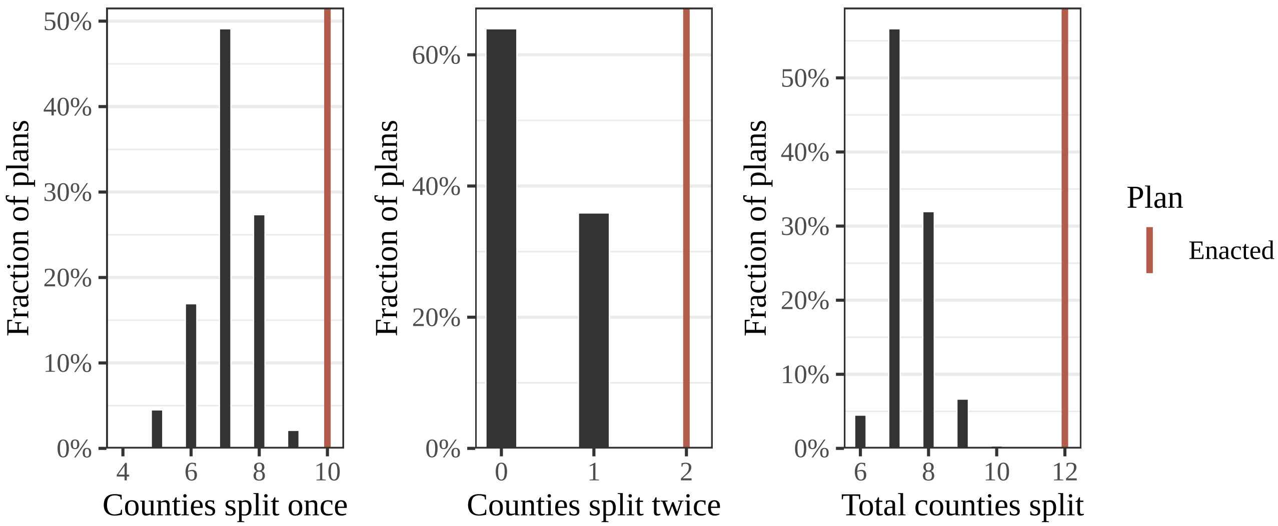

Figure 8: The number of county splits for the simulated redistricting plans. Overlaid are the scores for the enacted plan (red). The left plot shows the number of counties that are split once under each plan, whereas the middle plot presents the number of counties that are split twice under each plan. The right plot shows the number of counties that are split either once or twice. No county is split more than twice under both the enacted plan and any of the simulated plans.

- The six statewide federal elections I use to implement the General Assembly's approach: US President (2012, 2016, 2020), US Senate (2012, 2016, 2018)

- The 2016, 2018, and 2020 precinct-level shapefiles were acquired from the Voting and Election Science Team at the University of Florida and Wichita State University. This data is publicly available on the Harvard Dataverse, an online repository of social science data. Those shapefiles were joined to precinct-level election returns from the Ohio Secretary of State's office, which had been processed and cleaned by OpenElections.

- The 2012 and 2014 election returns pro-rated to the 2010 VTD level were acquired from Bill Cooper. Counsel has informed that Bill Cooper provided the following description of the data: The 2012 results are disaggregated to the block level (based on block centroids) from the statewide 2012 precinct file. The 2014 results are based on a geocoding of about 3.15 million voters who cast ballots in Nov. 2014. These addresses were matched to census blocks and the blocks were aggregated to the precinct level. These virtual precincts were next matched to the 2014 election results and then disaggregated back to the block level, with block-level matches. When aggregated to the congressional level, the differences are measured in the tenths of a percent for House contests. As a final step, these datasets were aggregated from the block-level to the 2010 VTD level. Finally, it is important to note that there is a 2% to 3% undercount statewide for all votes cast in the 2014 election.

- Given the missing votes for the 2014 contests in Lorain County, the VTD-level totals in that county were approximated using the official precinct 2014 returns. First, after identifying the township, city, or village of each 2014 precinct, the official precinct-level returns were aggregated up to that level. Those municipality-level returns were then disaggregated for each candidate down to the VTDs in each municipality, proportionally to the vote counts for the candidate running for the same office and party in the 2018 midterm cycle.

- The 2020 Census Block shapefiles, total population by race and ethnicity, and voting age population by race and ethnicity were obtained directly from the Census FTP portal.

- The 2020 Census place block assignment files (for city and village boundaries and VTD block assignment files) were obtained from the Census website.

- The 2020 Census county subdivision shapefiles (for Ohio township boundaries) were obtained from the Census website.

- The enacted plan data were gathered from the text of SB258, and cleaned into a block equivalency file.

- Geolocated congressional incumbent names and addresses, which were gathered by Carl Klarner, were acquired through Redistricting Data Hub. For new incumbents who came into office following the 2021 general election (Shontel Brown, Mike Carey), their addresses and geolocated locations were given to me by counsel for the plaintiffs.

Data Processing

- The datasets that were on the 2020 census block level (total population, voting age population, Census place assignment, VTD assignment, enacted plan) were joined to the 2020 Census block shapefile.

- The datasets that were not on the level of the census block (2016, 2018, and 2020 election returns – precinct; 2012 and 2014 election returns – 2010 VTD) were disaggregated down to the 2020 census block level. Then, the resulting data were joined to the 2020 Census block shapefile.

- For the 2020 Census county subdivision shapefile, each 2020 Census block was assigned to its corresponding county subdivision assignment by overlaying the county subdivision shapefile onto the 2020 Census blocks.

- Given that some of Ohio's voting districts are geographically discontiguous, the separate discontiguous pieces of each voting district were identified.

Data Aggregation

- The full block-level dataset was aggregated up to the level of the 2020 voting districts, taking into account (a) discontiguous voting districts and (b) splits of voting districts by the enacted plan.

- The final municipality ID was constructed on the aggregated dataset. Where a VTD belonged to a village or a city, the municipality ID took the value of that village or city. Otherwise, it took the value of the county subdivision of the VTD. Then, discontiguous municipalities or townships were identified, and assigned to unique identifiers. The final municipality ID concatenates the original municipality ID, the identifier for each discontiguous piece, and a county identifier, so that it identifies a unique contiguous piece of a municipality within a given county.

E.2. References

Autry, Eric, Daniel Carter, Gregory Herschlag, Zach Hunter, and Jonathan Mattingly. 2020. "Multi-scale merge-split Markov chain Monte Carlo for Redistricting." *arXiv preprint arXiv:2008.08054.*

Carter, Daniel, Gregory Herschlag, Zach Hunter, and Jonathan Mattingly. 2019. "A Merge-Split Proposal for Reversible Monte Carlo Markov Chain Sampling of Redistricting Plans." *arXiv preprint arXiv:1911.01503.*

DeFord, Daryl, Moon Duchin, and Justin Solomon. 2021. "Recombination: A Family of Markov Chains for Redistricting." Https://hdsr.mitpress.mit.edu/pub/1ds8ptxu, *Harvard Data Science Review* (March 31, 2021). https://doi.org/10.1162/99608f92.eb30390f. https://hdsr.mitpress.mit.edu/pub/1ds8ptxu.

Doucet, Arnaud, Nando de Freitas, and Neil Gordon. 2001. *Sequential Monte Carlo methods in practice.* New York: Springer.

Fifield, Benjamin, Michael Higgins, Kosuke Imai, and Alexander Tarr. 2020. "Automated Redistricting Simulation Using Markov Chain Monte Carlo." *Journal of Computational and Graphical Statistics* 29 (4): 715–728.

Fifield, Benjamin, Kosuke Imai, Jun Kawahara, and Christopher T Kenny. 2020. "The essential role of empirical validation in legislative redistricting simulation." *Statistics and Public Policy* 7 (1): 52–68.

Gilks, Walter R., Sylvia Richardson, and David J. Spiegelhalter. 1996. *Markov chain Monte Carlo in Practice.* London: Chapman & Hall.

Herschlag, Gregory, Han Sung Kang, Justin Luo, Christy Vaughn Graves, Sachet Bangia, Robert Ravier, and Jonathan C Mattingly. 2020. "Quantifying gerrymandering in North Carolina: Supplemental Appendix." *Statistics and Public Policy* 7 (1): 30–38.

Imai, Kosuke, and Kabir Khanna. 2016. "Improving Ecological Inference by Predicting Individual Ethnicity from Voter Registration Record." *Political Analysis* 24 (2): 263–272.

Imai, Kosuke, Ying Lu, and Aaron Strauss. 2008. "Bayesian and Likelihood Inference for 2×2 Ecological Tables: An Incomplete Data Approach." *Political Analysis* 16 (1): 41–69.

Kenny, Christopher T., Shiro Kuriwaki, Cory McCartan, Evan Rosenman, Tyler Simko, and Kosuke Imai. 2021. "The Use of Differential Privacy for Census Data and its Impact on Redistricting: The Case of the 2020 U.S. Census." *Science Advances* 7, no. 41 (October): 1–17.

Kenny, Christopher T., Cory McCartan, Benjamin Fifield, and Kosuke Imai. 2020. *redist: Computational Algorithms for Redistricting Simulation.* https://CRAN.R-project.org/package=redist.

McCartan, Cory, and Kosuke Imai. 2020. "Sequential Monte Carlo for sampling balanced and compact redistricting plans." *arXiv preprint arXiv:2008.06131.*

Polsby, Daniel D, and Robert D Popper. 1991. "The third criterion: Compactness as a procedural safeguard against partisan gerrymandering." *Yale Law & Policy Review* 9 (2): 301–353.

Tukey, John W. 1977. *Exploratory Data Analysis.* Pearson.

EXHIBIT A

Curriculum Vitae

Kosuke Imai

Curriculum Vitae

November 2021

Contact Information

1737 Cambridge Street
Institute for Quantitative Social Science
Harvard University
Cambridge, MA 02138

Phone: 617-384-6778
Email: Imai@Harvard.Edu
URL: https://imai.fas.harvard.edu

Education

Ph.D. in Political Science, Harvard University (1999–2003)

A.M. in Statistics, Harvard University (2000–2002)

B.A. in Liberal Arts, The University of Tokyo (1994–1998)

Positions

Professor, Department of Government and Department of Statistics, Harvard University (2018 – present)

Professor, Department of Politics and Center for Statistics and Machine Learning, Princeton University (2013 – 2018)

> Founding Director, Program in Statistics and Machine Learning (2013 – 2017)

Professor of Visiting Status, Graduate Schools of Law and Politics, The University of Tokyo (2016 – present)

Associate Professor, Department of Politics, Princeton University (2012 – 2013)

Assistant Professor, Department of Politics, Princeton University (2004 – 2012)

Visiting Researcher, Faculty of Economics, The University of Tokyo (August, 2006)

Instructor, Department of Politics, Princeton University (2003 – 2004)

Honors and Awards

1. Invited to read "Experimental Evaluation of Computer-Assisted Human Decision-Making: Application to Pretrial Risk Assessment Instrument." before the Royal Statistical Society Research Section, London (2021).

2. *Excellence in Mentoring Award*, awarded by the Society for Political Methodology (2021).

3. *Statistical Software Award* for developing statistical software that makes a significant research contribution, for "fastLink: Fast Probabilistic Record Linkage," awarded by the Society for Political Methodology (2021).

4. *Highly Cited Researcher* (cross-field category) for "production of multiple highly cited papers that rank in the top 1% by citations for field and year in Web of Science," awarded by Clarivate Analytics (2018, 2019, 2020).

5. *President*, The Society for Political Methodology (2017–2019). *Vice President and President-elect* (2015–2017).

6. *Elected Fellow*, The Society for Political Methodology (2017).

7. *The Nils Petter Gleditsch Article of the Year Award* (2017), awarded by *Journal of Peace Research.*

8. *Statistical Software Award* for developing statistical software that makes a significant research contribution, for "mediation: R Package for Causal Mediation Analysis," awarded by the Society for Political Methodology (2015).

9. *Outstanding Reviewer Award* for Journal of Educational and Behavioral Statistics, given by the American Educational Research Association (2014).

10. *The Stanley Kelley, Jr. Teaching Award*, given by the Department of Politics, Princeton University (2013).

11. *Pi Sigma Alpha Award* for the best paper presented at the 2012 Midwest Political Science Association annual meeting, for "Explaining Support for Combatants during Wartime: A Survey Experiment in Afghanistan," awarded by the Midwest Political Science Association (2013).

12. Invited to read "Experimental Designs for Identifying Causal Mechanisms" before the Royal Statistical Society Research Section, London (2012).

13. Inaugural recipient of the *Emerging Scholar Award* for a young scholar making exceptional contributions to political methodology who is within ten years of their terminal degree, awarded by the Society for Political Methodology (2011).

14. *Political Analysis Editors' Choice Award* for an article providing an especially significant contribution to political methodology, for "Estimation of Heterogeneous Treatment Effects from Randomized Experiments, with Application to the Optimal Planning of the Get-out-the-vote Campaign," awarded by the Society for Political Methodology and Oxford University Press (2011).

ADAMS_00090

15. *Tom Ten Have Memorial Award* for the best poster presented at the 2011 Atlantic Causal Inference Conference, for "Identifying Treatment Effect Heterogeneity through Optimal Classification and Variable Selection," awarded by the Departments of Biostatistics and Statistics, University of Michigan (2011).

16. Nominated for the *Graduate Mentoring Award*, The McGraw Center for Teaching and Learning, Princeton University (2010, 2011).

17. *New Hot Paper*, for the most-cited paper in the field of Economics & Business in the last two months among papers published in the last year, for "Misunderstandings among Experimentalists and Observationalists about Causal Inference," named by Thomson Reuters' ScienceWatch (2009).

18. *Warren Miller Prize* for the best article published in *Political Analysis*, for "Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference," awarded by the Society for Political Methodology and Oxford University Press (2008).

19. *Fast Breaking Paper* for the article with the largest percentage increase in citations among those in the top 1% of total citations across the social sciences in the last two years, for "Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference," named by Thomson Reuters' ScienceWatch (2008).

20. *Pharmacoepidemiology and Drug Safety Outstanding Reviewer Recognition* (2008).

21. *Miyake Award* for the best political science article published in 2005, for "Do Get-Out-The-Vote Calls Reduce Turnout? The Importance of Statistical Methods for Field Experiments," awarded by the Japanese Political Science Association (2006).

22. *Toppan Prize* for the best dissertation in political science, for *Essays on Political Methodology*, awarded by Harvard University (2004). Also, nominated for American Political Science Association E.E. Schattschneider Award for the best doctoral dissertation in the field of American government and politics.

Publications in English

Book

Imai, Kosuke. (2017). *Quantitative Social Science: An Introduction.* Princeton University Press. Translated into Japanese (2018), Chinese (2020), and Korean (2021).

Stata version (2021) with Lori D. Bougher.

Tidyverse version (forthcoming) with Nora Webb Williams

Refereed Journal Articles

1. Fan, Jianqing, Kosuke Imai, Inbeom Lee, Han Liu, Yang Ning, and Xiaolin Yang. "Optimal Covariate Balancing Conditions in Propensity Score Estimation." *Journal of Business & Economic Statistics*, Forthcoming.

ADAMS_00091

2. Imai, Kosuke, Zhichao Jiang, D. James Greiner, Ryan Halen, and Sooahn Shin. "Experimental Evaluation of Computer-Assisted Human Decision-Making: Application to Pretrial Risk Assessment Instrument." (with discussion) *Journal of the Royal Statistical Society, Series A (Statistics in Society)*, Forthcoming. To be read before the Royal Statistical Society.

3. Imai, Kosuke, In Song Kim, and Erik Wang. "Matching Methods for Causal Inference with Time-Series Cross-Sectional Data." *American Journal of Political Science*, Forthcoming.

4. Imai, Kosuke and Michael Lingzhi Li. "Experimental Evaluation of Individualized Treatment Rules." *Journal of the American Statistical Association*, Forthcoming.

5. de la Cuesta, Brandon, Naoki Egami, and Kosuke Imai."Experimental Design and Statistical Inference for Conjoint Analysis: The Essential Role of Population Distribution." *Political Analysis*, Forthcoming.

6. Kenny, Christopher T., Shiro Kuriwaki, Cory McCartan, Evan Rosenman, Tyler Simko, and Kosuke Imai. (2021). "The Use of Differential Privacy for Census Data and its Impact on Redistricting: The Case of the 2020 U.S. Census." *Science Advances*, Vol. 7, No. 7 (October), pp. 1-17.

7. Imai, Kosuke and James Lo. (2021). " Robustness of Empirical Evidence for the Democratic Peace: A Nonparametric Sensitivity Analysis." *International Organization*, Vol. 75, No. 3 (Summer), pp. 901–919.

8. Imai, Kosuke, Zhichao Jiang, and Anup Malani. (2021). "Causal Inference with Interference and Noncompliance in the Two-Stage Randomized Experiments." *Journal of the American Statistical Association*, Vol. 116, No. 534, pp. 632-644.

9. Imai, Kosuke, and In Song Kim. (2021). "On the Use of Two-way Fixed Effects Regression Models for Causal Inference with Panel Data." *Political Analysis*, Vol. 29, No. 3 (July), pp. 405–415.

10. Imai, Kosuke and Zhichao Jiang. (2020). "Identification and Sensitivity Analysis of Contagion Effects with Randomized Placebo-Controlled Trials." *Journal of the Royal Statistical Society, Series A (Statistics in Society)*, Vol. 183, No. 4 (October), pp. 1637–1657.

11. Fifield, Benjamin, Michael Higgins, Kosuke Imai, and Alexander Tarr. (2020). "Automated Redistricting Simulation Using Markov Chain Monte Carlo." *Journal of Computational and Graphical Statistics*, Vol. 29, No. 4, pp. 715–728.

12. Fifield, Benjamin, Kosuke Imai, Jun Kawahara, and Christopher T. Kenny. (2020). "The Essential Role of Empirical Validation in Legislative Redistricting Simulation." *Statistics and Public Policy*, Vol. 7, No 1, pp. 52–68.

13. Ning, Yang, Sida Peng, and Kosuke Imai. (2020). "Robust Estimation of Causal Effects via High-Dimensional Covariate Balancing Propensity Score." *Biometrika*, Vol. 107, No. 3 (September), pp. 533—554.

ADAMS_00092

14. Chou, Winston, Kosuke Imai, and Bryn Rosenfeld. (2020). "Sensitive Survey Questions with Auxiliary Information." *Sociological Methods & Research*, Vol. 49, No. 2 (May), pp. 418–454.

15. Imai, Kosuke, Gary King, and Carlos Velasco Rivera. (2020). "Do Nonpartisan Programmatic Policies Have Partisan Electoral Effects? Evidence from Two Large Scale Randomized Experiments." *Journal of Politics*, Vol. 82, No. 2 (April), pp. 714–730.

16. Zhao, Shandong, David A. van Dyk, and Kosuke Imai. (2020). "Propensity-Score Based Methods for Causal Inference in Observational Studies with Non-Binary Treatments." *Statistical Methods in Medical Research*, Vol. 29, No. 3 (March), pp. 709–727.

17. Lyall, Jason, Yang-Yang Zhou, and Kosuke Imai. (2020). "Can Economic Assistance Shape Combatant Support in Wartime? Experimental Evidence from Afghanistan." *American Political Science Review*, Vol. 114, No. 1 (February), pp. 126–143.

18. Kim, In Song, Steven Liao, and Kosuke Imai. (2020). "Measuring Trade Profile with Granular Product-level Trade Data." *American Journal of Political Science*, Vol. 64, No. 1 (January), pp. 102-117.

19. Enamorado, Ted and Kosuke Imai. (2019). "Validating Self-reported Turnout by Linking Public Opinion Surveys with Administrative Records." *Public Opinion Quarterly*, Vol. 83, No. 4 (Winter), pp. 723—748.

20. Blair, Graeme, Winston Chou, and Kosuke Imai. (2019). "List Experiments with Measurement Error." *Political Analysis*, Vol. 27, No. 4 (October), pp. 455–480.

21. Egami, Naoki, and Kosuke Imai. "Causal Interaction in Factorial Experiments: Application to Conjoint Analysis." *Journal of the American Statistical Association*, Vol. 114, No. 526 (June), pp. 529-540.

22. Enamorado, Ted, Benjamin Fifield, and Kosuke Imai. (2019). "Using a Probabilistic Model to Assist Merging of Large-scale Administrative Records." *American Political Science Review*, Vol. 113, No. 2 (May), pp. 353–371.

23. Imai, Kosuke and In Song Kim. (2019) "When Should We Use Linear Fixed Effects Regression Models for Causal Inference with Longitudinal Data?." *American Journal of Political Science*, Vol. 63, No. 2 (April), pp. 467–490.

24. Imai, Kosuke, and Zhichao Jiang. (2018). "A Sensitivity Analysis for Missing Outcomes Due to Truncation-by-Death under the Matched-Pairs Design." *Statistics in Medicine*, Vol. 37, No. 20 (September), pp. 2907–2922.

25. Fong, Christian, Chad Hazlett, and Kosuke Imai. (2018). "Covariate Balancing Propensity Score for a Continuous Treatment: Application to the Efficacy of Political Advertisements." *Annals of Applied Statistics*, Vol. 12, No. 1, pp. 156–177.

26. Hirose, Kentaro, Kosuke Imai, and Jason Lyall. (2017). "Can Civilian Attitudes Predict Insurgent Violence?: Ideology and Insurgent Tactical Choice in Civil War" *Journal of Peace Research*, Vol. 51, No. 1 (January), pp. 47–63.

ADAMS_00093

27. Imai, Kosuke, James Lo, and Jonathan Olmsted. (2016). "Fast Estimation of Ideal Points with Massive Data." *American Political Science Review*, Vol. 110, No. 4 (December), pp. 631–656.

28. Rosenfeld, Bryn, Kosuke Imai, and Jacob Shapiro. (2016). "An Empirical Validation Study of Popular Survey Methodologies for Sensitive Questions." *American Journal of Political Science*, Vol. 60, No. 3 (July), pp. 783–802.

29. Imai, Kosuke and Kabir Khanna. (2016). "Improving Ecological Inference by Predicting Individual Ethnicity from Voter Registration Record." *Political Analysis*, Vol. 24, No. 2 (Spring), pp. 263–272.

30. Blair, Graeme, Kosuke Imai, and Yang-Yang Zhou. (2015). "Design and Analysis of the Randomized Response Technique." *Journal of the American Statistical Association*, Vol. 110, No. 511 (September), pp. 1304–1319.

31. Imai, Kosuke and Marc Ratkovic. (2015). "Robust Estimation of Inverse Probability Weights for Marginal Structural Models." *Journal of the American Statistical Association*, Vol. 110, No. 511 (September), pp. 1013–1023. (lead article)

32. Lyall, Jason, Yuki Shiraito, and Kosuke Imai. (2015). "Coethnic Bias and Wartime Informing." *Journal of Politics*, Vol. 77, No. 3 (July), pp. 833–848.

33. Imai, Kosuke, Bethany Park, and Kenneth Greene. (2015). "Using the Predicted Responses from List Experiments as Explanatory Variables in Regression Models." *Political Analysis*, Vol. 23, No. 2 (Spring), pp. 180–196. Translated in Portuguese and Reprinted in *Revista Debates* Vol. 9, No 1.

34. Blair, Graeme, Kosuke Imai, and Jason Lyall. (2014). "Comparing and Combining List and Endorsement Experiments: Evidence from Afghanistan." *American Journal of Political Science*, Vol. 58, No. 4 (October), pp. 1043–1063.

35. Tingley, Dustin, Teppei Yamamoto, Kentaro Hirose, Luke Keele, and Kosuke Imai. (2014). "mediation: R Package for Causal Mediation Analysis." *Journal of Statistical Software*, Vol. 59, No. 5 (August), pp. 1–38.

36. Imai, Kosuke and Marc Ratkovic. (2014). "Covariate Balancing Propensity Score." *Journal of the Royal Statistical Society, Series B (Statistical Methodology)*, Vol. 76, No. 1 (January), pp. 243–263.

37. Lyall, Jason, Graeme Blair, and Kosuke Imai. (2013). "Explaining Support for Combatants during Wartime: A Survey Experiment in Afghanistan." *American Political Science Review*, Vol. 107, No. 4 (November), pp. 679-705. Winner of the Pi Sigma Alpha Award.

38. Imai, Kosuke and Teppei Yamamoto. (2013). "Identification and Sensitivity Analysis for Multiple Causal Mechanisms: Revisiting Evidence from Framing Experiments." *Political Analysis*, Vol. 21, No. 2 (Spring), pp. 141–171. (lead article).

39. Imai, Kosuke and Marc Ratkovic. (2013). "Estimating Treatment Effect Heterogeneity in Randomized Program Evaluation." *Annals of Applied Statistics*, Vol. 7, No. 1 (March), pp. 443–470. Winner of the Tom Ten Have Memorial Award. Reprinted in *Advances in Political Methodology*, R. Franzese, Jr. ed., Edward Elger, 2017.

ADAMS_00094

40. Imai, Kosuke, Dustin Tingley, and Teppei Yamamoto. (2013). "Experimental Designs for Identifying Causal Mechanisms."(with discussions) *Journal of the Royal Statistical Society, Series A (Statistics in Society)*, Vol. 176, No. 1 (January), pp. 5–51. (lead article) Read before the Royal Statistical Society, March 2012.

41. Imai, Kosuke, and Dustin Tingley. (2012). "A Statistical Method for Empirical Testing of Competing Theories." *American Journal of Political Science*, Vol. 56, No. 1 (January), pp. 218–236.

42. Blair, Graeme, and Kosuke Imai. (2012). "Statistical Analysis of List Experiments." *Political Analysis*, Vol. 20, No. 1 (Winter), pp. 47–77.

43. Imai, Kosuke, Luke Keele, Dustin Tingley, and Teppei Yamamoto. (2011). "Unpacking the Black Box of Causality: Learning about Causal Mechanisms from Experimental and Observational Studies." *American Political Science Review*, Vol. 105, No. 4 (November), pp. 765–789. Reprinted in *Advances in Political Methodology*, R. Franzese, Jr. ed., Edward Elger, 2017.

44. Bullock, Will, Kosuke Imai, and Jacob N. Shapiro. (2011). "Statistical Analysis of Endorsement Experiments: Measuring Support for Militant Groups in Pakistan." *Political Analysis*, Vol. 19, No. 4 (Autumn), pp. 363–384. (lead article)

45. Imai, Kosuke. (2011). "Multivariate Regression Analysis for the Item Count Technique." *Journal of the American Statistical Association*, Vol. 106, No. 494 (June), pp. 407–416. (featured article)

46. Ho, Daniel E., Kosuke Imai, Gary King, and Elizabeth Stuart. (2011). "MatchIt: Nonparametric Preprocessing for Parametric Causal Inference." *Journal of Statistical Software*, Vol. 42 (Special Volume on Political Methodology), No. 8 (June), pp. 1–28.

47. Imai, Kosuke, Ying Lu, and Aaron Strauss. (2011). "eco: R Package for Ecological Inference in 2×2 Tables." *Journal of Statistical Software*, Vol. 42 (Special Volume on Political Methodology), No. 5 (June), pp. 1–23.

48. Imai, Kosuke and Aaron Strauss. (2011). "Estimation of Heterogeneous Treatment Effects from Randomized Experiments, with Application to the Optimal Planning of the Get-out-the-vote Campaign." *Political Analysis*, Vol. 19, No. 1 (Winter), pp. 1–19. (lead article) Winner of the Political Analysis Editors' Choice Award.

49. Imai, Kosuke, Luke Keele, and Dustin Tingley. (2010). "A General Approach to Causal Mediation Analysis." *Psychological Methods*, Vol. 15, No. 4 (December), pp. 309–334. (lead article)

50. Imai, Kosuke and Teppei Yamamoto. (2010). "Causal Inference with Differential Measurement Error: Nonparametric Identification and Sensitivity Analysis." *American Journal of Political Science*, Vol. 54, No. 2 (April), pp. 543–560.

51. Imai, Kosuke, Luke Keele, and Teppei Yamamoto. (2010). "Identification, Inference, and Sensitivity Analysis for Causal Mediation Effects." *Statistical Science*, Vol. 25, No. 1 (February), pp. 51–71.

ADAMS_00095

52. King, Gary, Emmanuela Gakidou, Kosuke Imai, Jason Lakin, Ryan T. Moore, Clayton Nall, Nirmala Ravishankar, Manett Vargas, Martha María Téllez-Rojo, Juan Eugenio Hernández Ávila, Mauricio Hernández Ávila, and Héctor Hernández Llamas. (2009). "Public Policy for the Poor? A Randomized Ten-Month Evaluation of the Mexican Universal Health Insurance Program." (with a comment) *The Lancet*, Vol. 373, No. 9673 (April), pp. 1447–1454.

53. Imai, Kosuke, Gary King, and Clayton Nall. (2009). "The Essential Role of Pair Matching in Cluster-Randomized Experiments, with Application to the Mexican Universal Health Insurance Evaluation." (with discussions) *Statistical Science*, Vol. 24, No. 1 (February), pp. 29–53.

54. Imai, Kosuke. (2009). "Statistical Analysis of Randomized Experiments with Nonignorable Missing Binary Outcomes: An Application to a Voting Experiment." *Journal of the Royal Statistical Society, Series C (Applied Statistics)*, Vol. 58, No. 1 (February), pp. 83–104.

55. Imai, Kosuke, Gary King, and Olivia Lau. (2008). "Toward A Common Framework of Statistical Analysis and Development." *Journal of Computational and Graphical Statistics*, Vol. 17, No. 4 (December), pp. 892–913.

56. Imai, Kosuke. (2008). "Variance Identification and Efficiency Analysis in Experiments under the Matched-Pair Design." *Statistics in Medicine*, Vol. 27, No. 4 (October), pp. 4857–4873.

57. Ho, Daniel E., and Kosuke Imai. (2008). "Estimating Causal Effects of Ballot Order from a Randomized Natural Experiment: California Alphabet Lottery, 1978–2002." *Public Opinion Quarterly*, Vol. 72, No. 2 (Summer), pp. 216–240.

58. Imai, Kosuke, Gary King, and Elizabeth A. Stuart. (2008). "Misunderstandings among Experimentalists and Observationalists: Balance Test Fallacies in Causal Inference." *Journal of the Royal Statistical Society, Series A (Statistics in Society)*, Vol. 171, No. 2 (April), pp. 481–502. Reprinted in *Field Experiments and their Critics*, D. Teele ed., New Haven: Yale University Press, 2013.

59. Imai, Kosuke, Ying Lu, and Aaron Strauss. (2008). "Bayesian and Likelihood Ecological Inference for 2×2 Tables: An Incomplete Data Approach." *Political Analysis*, Vol. 16, No. 1 (Winter), pp. 41–69.

60. Imai, Kosuke. (2008). "Sharp Bounds on the Causal Effects in Randomized Experiments with "Truncation-by-Death"." *Statistics & Probability Letters*, Vol. 78, No. 2 (February), pp. 144–149.

61. Imai, Kosuke and Samir Soneji. (2007). "On the Estimation of Disability-Free Life Expectancy: Sullivan's Method and Its Extension." *Journal of the American Statistical Association*, Vol. 102, No. 480 (December), pp. 1199–1211.

62. Horiuchi, Yusaku, Kosuke Imai, and Naoko Taniguchi. (2007). "Designing and Analyzing Randomized Experiments: Application to a Japanese Election Survey Experiment." *American Journal of Political Science*, Vol. 51, No. 3 (July), pp. 669–687.

ADAMS_00096

63. Ho, Daniel E., Kosuke Imai, Gary King, and Elizabeth A. Stuart. (2007). "Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference." *Political Analysis*, Vol. 15, No. 3 (Summer), pp. 199–236. (lead article) Winner of the Warren Miller Prize.

64. Ho, Daniel E., and Kosuke Imai. (2006). "Randomization Inference with Natural Experiments: An Analysis of Ballot Effects in the 2003 California Recall Election." *Journal of the American Statistical Association*, Vol. 101, No. 475 (September), pp. 888–900.

65. Imai, Kosuke, and David A. van Dyk. (2005). "MNP: R Package for Fitting the Multinomial Probit Model." *Journal of Statistical Software*, Vol. 14, No. 3 (May), pp. 1–32. abstract reprinted in *Journal of Computational and Graphical Statistics* (2005) Vol. 14, No. 3 (September), p. 747.

66. Imai, Kosuke. (2005). "Do Get-Out-The-Vote Calls Reduce Turnout? The Importance of Statistical Methods for Field Experiments." *American Political Science Review*, Vol. 99, No. 2 (May), pp. 283–300.

67. Imai, Kosuke, and David A. van Dyk. (2005). "A Bayesian Analysis of the Multinomial Probit Model Using Marginal Data Augmentation." *Journal of Econometrics*, Vol. 124, No. 2 (February), pp. 311–334.

68. Imai, Kosuke, and David A. van Dyk. (2004). "Causal Inference With General Treatment Regimes: Generalizing the Propensity Score." *Journal of the American Statistical Association*, Vol. 99, No. 467 (September), pp. 854–866.

69. Imai, Kosuke, and Gary King. (2004). "Did Illegal Overseas Absentee Ballots Decide the 2000 U.S. Presidential Election?" *Perspectives on Politics*, Vol. 2, No. 3 (September), pp. 537–549. Our analysis is a part of *The New York Times* article, "How Bush Took Florida: Mining the Overseas Absentee Vote" By David Barstow and Don van Natta Jr. July 15, 2001, Page 1, Column 1.

Invited Contributions

1. Imai, Kosuke, and Zhichao Jiang. (2019). "Comment: The Challenges of Multiple Causes." *Journal of the American Statistical Association*, Vol. 114, No. 528, pp. 1605—1610.

2. Benjamin, Daniel J., *et al.* (2018). "Redefine Statistical Significance." *Nature Human Behaviour*, Vol. 2, No. 1, pp. 6–10.

3. de la Cuesta, Brandon and Kosuke Imai. (2016). "Misunderstandings about the Regression Discontinuity Design in the Study of Close Elections." *Annual Review of Political Science*, Vol. 19, pp. 375–396.

4. Imai, Kosuke (2016). "Book Review of *Causal Inference for Statistics, Social, and Biomedical Sciences: An Introduction.* by Guido W. Imbens and Donald B. Rubin." *Journal of the American Statistical Association*, Vol. 111, No. 515, pp. 1365–1366.

5. Imai, Kosuke, Bethany Park, and Kenneth F. Greene. (2015). "Usando as respostas previsíveis da abordagem list-experiments como variaveis explicativás em modelos de regressão." *Revista Debates*, Vol. 9, No. 1, pp. 121–151. First printed in *Political Analysis*, Vol. 23, No. 2 (Spring).

ADAMS_00097

6. Imai, Kosuke, Luke Keele, Dustin Tingley, and Teppei Yamamoto. (2014). "Comment on Pearl: Practical Implications of Theoretical Results for Causal Mediation Analysis." *Psychological Methods*, Vol. 19, No. 4 (December), pp. 482–487.

7. Imai, Kosuke, Gary King, and Elizabeth A. Stuart. (2014). "Misunderstandings among Experimentalists and Observationalists: Balance Test Fallacies in Causal Inference." in *Field Experiments and their Critics: Essays on the Uses and Abuses of Experimentation in the Social Sciences*, D. L. Teele ed., New Haven: Yale University Press, pp. 196–227. First printed in *Journal of the Royal Statistical Society, Series A (Statistics in Society)*, Vol. 171, No. 2 (April).

8. Imai, Kosuke, Dustin Tingley, and Teppei Yamamoto. (2013). "Reply to Discussions of "Experimental Designs for Identifying Causal Mechanisms"." *Journal of the Royal Statistical Society, Series A (Statistics in Society)*, Vol. 173, No. 1 (January), pp. 46–49.

9. Imai, Kosuke. (2012). "Comments: Improving Weighting Methods for Causal Mediation Analysis." *Journal of Research on Educational Effectiveness*, Vol. 5, No. 3, pp. 293–295.

10. Imai, Kosuke. (2011). "Introduction to the Virtual Issue: Past and Future Research Agenda on Causal Inference." *Political Analysis*, Virtual Issue: Causal Inference and Political Methodology.

11. Imai, Kosuke, Booil Jo, and Elizabeth A. Stuart. (2011). "Commentary: Using Potential Outcomes to Understand Causal Mediation Analysis." *Multivariate Behavioral Research*, Vol. 46, No. 5, pp. 842–854.

12. Imai, Kosuke, Luke Keele, Dustin Tingley, and Teppei Yamamoto. (2010). "Causal Mediation Analysis Using R," in *Advances in Social Science Research Using R*, H. D. Vinod (ed.), New York: Springer (Lecture Notes in Statistics), pp. 129–154.

13. Imai, Kosuke, Gary King, and Clayton Nall. (2009). "Rejoinder: Matched Pairs and the Future of Cluster-Randomized Experiments." *Statistical Science*, Vol. 24, No. 1 (February), pp. 65–72.

14. Imai, Kosuke. (2003). "Review of Jeff Gill's *Bayesian Methods: A Social and Behavioral Sciences Approach*," *The Political Methodologist*, Vol. 11 No. 1, 9–10.

Refereed Conference Proceedings

1. Svyatkovskiy, Alexey, Kosuke Imai, Mary Kroeger, and Yuki Shiraito. (2016). "Large-scale text processing pipeline with Apache Spark," *IEEE International Conference on Big Data*, Washington, DC, pp. 3928-3935.

Other Publications and Manuscripts

1. Goldstein, Daniel, Kosuke Imai, Anja S. Göritz, and Peter M. Gollwitzer. (2008). "Nudging Turnout: Mere Measurement and Implementation Planning of Intentions to Vote."

2. Ho, Daniel E. and Kosuke Imai. (2004). " The Impact of Partisan Electoral Regulation: Ballot Effects from the California Alphabet Lottery, 1978–2002." Princeton Law & Public Affairs Paper No. 04-001; Harvard Public Law Working Paper No. 89.

ADAMS_00098

3. Imai, Kosuke. (2003). "Essays on Political Methodology," *Ph.D. Thesis.* Department of Government, Harvard University.

4. Imai, Kosuke, and Jeremy M. Weinstein. (2000). "Measuring the Economic Impact of Civil War," Working Paper Series No. 51, Center for International Development, Harvard University.

Selected Manuscripts

1. McCartan, Cory, Jacob Brown, and Kosuke Imai. "Measuring and Modeling Neighborhoods."

2. Ben-Michael, Eli, D. James Greiner, Kosuke Imai, and Zhichao Jiang. "Safe Policy Learning through Extrapolation: Application to Pre-trial Risk Assessment."

3. Tarr, Alexander and Kosuke Imai. "Estimating Average Treatment Effects with Support Vector Machines."

4. McCartan, Cory and Kosuke Imai. "Sequential Monte Carlo for Sampling Balanced and Compact Redistricting Plans."

5. Imai, Kosuke and Zhichao Jiang. "Principal Fairness for Human and Algorithmic Decision-Making."

6. Papadogeorgou, Georgia, Kosuke Imai, Jason Lyall, and Fan Li. "Causal Inference with Spatio-temporal Data: Estimating the Effects of Airstrikes on Insurgent Violence in Iraq."

7. Eshima, Shusei, Kosuke Imai, and Tomoya Sasaki. "Keyword Assisted Topic Models."

8. Tarr, Alexander, June Hwang, and Kosuke Imai. "Automated Coding of Political Campaign Advertisement Videos: An Empirical Validation Study."

9. Olivella, Santiago, Tyler Pratt, and Kosuke Imai. "Dynamic Stochastic Blockmodel Regression for Social Networks: Application to International Conflicts."

10. Chan, K.C.G, K. Imai, S.C.P. Yam, Z. Zhang. "Efficient Nonparametric Estimation of Causal Mediation Effects."

11. Barber, Michael and Kosuke Imai. "Estimating Neighborhood Effects on Turnout from Geocoded Voter Registration Records."

12. Hirano, Shigeo, Kosuke Imai, Yuki Shiraito, and Masaki Taniguchi. "Policy Positions in Mixed Member Electoral Systems: Evidence from Japan."

Publications in Japanese

1. Imai, Kosuke. (2007). "Keiryō Seijigaku niokeru Ingateki Suiron (Causal Inference in Quantitative Political Science)." *Leviathan*, Vol. 40, Spring, pp. 224–233.

2. Horiuchi, Yusaku, Kosuke Imai, and Naoko Taniguchi. (2005). "Seisaku Jyōhō to Tōhyō Sanka: Field Jikken ni yoru Kensyō (Policy Information and Voter Participation: A Field Experiment)." *Nenpō Seijigaku (The Annals of the Japanese Political Science Association)*, 2005–I, pp. 161–180.

3. Taniguchi, Naoko, Yusaku Horiuchi, and Kosuke Imai. (2004). "Seitō Saito no Etsuran ha Tohyō Kōdō ni Eikyō Suruka? (Does Visiting Political Party Websites Influence Voting Behavior?)" *Nikkei Research Report*, Vol. IV, pp. 16–19.

Statistical Software

1. Eshima, Shusei, Kosuke Imai, and Tomoya Sasaki. "Keyword Assisted Topic Models." The Comprehensive R Archive Network and GitHub. 2020.

2. Li, Michael Lingzhi and Kosuke Imai. "evalITR: Evaluating Individualized Treatment Rules." available through The Comprehensive R Archive Network and GitHub. 2020.

3. Egami, Naoki, Brandon de la Cuesta, and Kosuke Imai. "factorEx: Design and Analysis for Factorial Experiments." available through The Comprehensive R Archive Network and GitHub. 2019.

4. Kim, In Song, Erik Wang, Adam Rauh, and Kosuke Imai. "PanelMatch: Matching Methods for Causal Inference with Time-Series Cross-Section Data." available through GitHub. 2018.

5. Olivella, Santiago, Adeline Lo, Tyler Pratt, and Kosuke Imai. "NetMix: Mixed-membership Regression Stochastic Blockmodel for Networks." available through CRAN and Github. 2019.

6. Enamorado, Ted, Benjamin Fifield, and Kosuke Imai. "fastLink: Fast Probabilistic Record Linkage." available through The Comprehensive R Archive Network and GitHub. Winner of the Statistical Software Award. 2017.

7. Khanna, Kabir, and Kosuke Imai. "wru: Who Are You? Bayesian Predictions of Racial Category Using Surname and Geolocation." available through The Comprehensive R Archive Network and GitHub. 2015.

8. Fifield, Benjamin, Christopher T. Kenny, Cory McCartan, and Kosuke Imai. "redist: Markov Chain Monte Carlo Methods for Redistricting Simulation." available through The Comprehensive R Archive Network and GitHub. 2015.

9. Imai, Kosuke, James Lo, and Jonathan Olmsted. "emIRT: EM Algorithms for Estimating Item Response Theory Models." available through The Comprehensive R Archive Network. 2015.

10. Blair, Graeme, Yang-Yang Zhou, and Kosuke Imai. "rr: Statistical Methods for the Randomized Response Technique." available through The Comprehensive R Archive Network and GitHub. 2015.

11. Fong, Christian, Marc Ratkovic, and Kosuke Imai. "CBPS: R Package for Covariate Balancing Propensity Score." available through The Comprehensive R Archive Network and GitHub. 2012.

12. Egami, Naoki, Marc Ratkovic, and Kosuke Imai. "FindIt: R Package for Finding Heterogeneous Treatment Effects." available through The Comprehensive R Archive Network and GitHub. 2012.

ADAMS_00100

13. Kim, In Song, and Kosuke Imai. "wfe: Weighted Linear Fixed Effects Regression Models for Causal Inference." available through The Comprehensive R Archive Network. 2011.

14. Shiraito, Yuki, and Kosuke Imai. "endorse: R Package for Analyzing Endorsement Experiments." available through The Comprehensive R Archive Network and GitHub. 2012.

15. Blair, Graeme, and Kosuke Imai. "list: Statistical Methods for the Item Count Technique and List Experiments." available through The Comprehensive R Archive Network and GitHub. 2011.

16. Tingley, Dustin, Teppei Yamamoto, Kentaro Hirose, Luke Keele, and Kosuke Imai. "mediation: R Package for Causal Mediation Analysis." available through The Comprehensive R Archive Network and GitHub. 2009. Winner of the Statistical Software Award. Reviewed in *Journal of Educational and Behavioral Statistics*.

17. Imai, Kosuke. "experiment: R Package for Designing and Analyzing Randomized Experiments." available through The Comprehensive R Archive Network. 2007.

18. Ho, Daniel E., Kosuke Imai, Gary King, and Elizabeth Stuart. "MatchIt: Nonparametric Preprocessing for Parametric Causal Inference." available through The Comprehensive R Archive Network and GitHub. 2005.

19. Imai, Kosuke, Ying Lu, and Aaron Strauss. "eco: Ecological Inference in 2×2 Tables." available through The Comprehensive R Archive Network and GitHub. 2004.

20. Imai, Kosuke, and David A. van Dyk. "MNP: R Package for Fitting the Multinomial Probit Model." available through The Comprehensive R Archive Network and GitHub. 2004.

21. Imai, Kosuke, Gary King, and Olivia Lau. "Zelig: Everyone's Statistical Software." available through The Comprehensive R Archive Network. 2004.

External Research Grants

Principal Investigator

1. National Science Foundation (2021–2024). "Collaborative Research: Causal Inference with Spatio-Temporal Data on Human Dynamics in Conflict Settings." (Algorithm for Threat Detection Program; DMS-2124463). Principal Investigator (with Georgia Papadogeorgou and Jason Lyall) $485,340.

2. National Science Foundation (2021–2023). "Evaluating the Impacts of Machine Learning Algorithms on Human Decisions." (Methodology, Measurement, and Statistics Program; SES-2051196). Principal Investigator (with D. James Greiner and Zhichao Jiang) $330,000.

3. Cisco Systems, Inc. (2020–2022). "Evaluating the Impacts of Algorithmic Recommendations on the Fairness of Human Decisions." (Ethics in AI; CG# 2370386) Principal Investigator (with D. James Greiner and Zhichao Jiang) $110,085.

4. The Alfred P. Sloan Foundation (2020–2022). "Causal Inference with Complex Treatment Regimes: Design, Identification, Estimation, and Heterogeneity." (Economics Program;

2020–13946) Co-Principal Investigator (with Francesca Dominici and Jose Zubizarreta) $996,299

5. Facebook Research Grant (2018). $25,000.
6. National Science Foundation (2016–2021). "Collaborative Conference Proposal: Support for Conferences and Mentoring of Women and Underrepresented Groups in Political Methodology." (Methodology, Measurement and Statistics and Political Science Programs; SES–1628102) Principal Investigator (with Jeffrey Lewis) $312,322. Supplement (SES–1831370) $60,000.
7. The United States Agency for International Development (2015–2017). "Unemployment and Insurgent Violence in Afghanistan: Evidence from the Community Development Program." (AID–OAA–A–12–00096) Principal Investigator (with Jason Lyall) $188,037
8. The United States Institute of Peace (2015–2016). "Assessing the Links between Economic Interventions and Stability: An impact evaluation of vocational and skills training in Kandahar, Afghanistan," Principal Investigator (with David Haines, Jon Kurtz, and Jason Lyall) $144,494.
9. Amazon Web Services in Education Research Grant (2014). Principal Investigator (with Graeme Blair and Carlos Velasco Rivera) $3,000.
10. Development Bank of Latin America (CAF) (2013). "The Origins of Citizen Support for Narcos: An Empirical Investigation," Principal Investigator (with Graeme Blair, Fabiana Machado, and Carlos Velasco Rivera). $15,000.
11. The International Growth Centre (2011–2013). "Poverty, Militancy, and Citizen Demands in Natural Resource-Rich Regions: Randomized Evaluation of the Oil Profits Dividend Plan for the Niger Delta" (RA–2010–12–013). Principal Investigator (with Graeme Blair). $117,116.
12. National Science Foundation, (2009–2012). "Statistical Analysis of Causal Mechanisms: Identification, Inference, and Sensitivity Analysis," (Methodology, Measurement, and Statistics Program and Political Science Program; SES–0918968). Principal Investigator. $97,574.
13. National Science Foundation, (2009–2011). "Collaborative Research: The Measurement and Identification of Media Priming Effects in Political Science," (Methodology, Measurement, and Statistics Program and Political Science Program; SES–0849715). Principal Investigator (with Nicholas Valentino). $317,126.
14. National Science Foundation, (2008–2009). "New Statistical Methods for Randomized Experiments in Political Science and Public Policy," (Political Science Program; SES–0752050). Principal Investigator. $52,565.
15. National Science Foundation, (2006–2009). "Collaborative Research: Generalized Propensity Score Methods," (Methodology, Measurement and Statistics Program; SES–0550873). Principal Investigator (with Donald B. Rubin and David A. van Dyk). $460,000.
16. The Telecommunications Advancement Foundation, (2004). "Analyzing the Effects of Party Webpages on Political Opinions and Voting Behavior," Principal Investigator (with Naoko Taniguchi and Yusaku Horiuchi). $12,000.

ADAMS_00102

Adviser and Statistical Consultant

1. National Science Foundation (2016–2017). "Doctoral Dissertation Research: Crossing Africa's Arbitrary Borders: How Refugees Shape National Boundaries by Challenging Them." (Political Science Program, SES–1560636). Principal Investigator and Adviser for Co-PI Yang-Yang Zhou's Dissertation Research. $18,900.

2. Institute of Education Sciences (2012–2014). "Academic and Behavioral Consequences of Visible Security Measures in Schools" (R305A120181). Statistical Consultant (Emily Tanner-Smith, Principal Investigator). $351,228.

3. National Science Foundation (2013–2014). "Doctoral Dissertation Research: Open Trade for Sale: Lobbying by Productive Exporting Firm" (Political Science Program, SES–1264090). Principal Investigator and Adviser for Co-PI In Song Kim's Dissertation Research. $22,540.

4. National Science Foundation (2012–2013). "Doctoral Dissertation Research: The Politics of Location in Resource Rent Distribution and the Projection of Power in Africa" (Political Science Program, SES–1260754). Principal Investigator and Adviser for Co-PI Graeme Blair's Dissertation Research. $17,640.

Invited Short Courses and Outreach Lectures

1. Short Course on Causal Inference and Statistics – Department of Political Science, Rice University, 2009; Institute of Political Science, Academia Sinica, 2014.

2. Short Course on Causal Inference and Identification, The Empirical Implications of Theoretical Models (EITM) Summer Institute – Harris School of Public Policy, University of Chicago, 2011; Department of Politics, Princeton University, 2012.

3. Short Course on Causal Mediation Analysis – Summer Graduate Seminar, Institute of Statistical Mathematics, Tokyo Japan, 2010; Society for Research on Educational Effectiveness Conference, Washington DC, Fall 2011, Spring 2012, Spring 2015; Inter-American Development Bank, 2012; Center for Education Research, University of Wisconsin, Madison, 2012; Bobst Center for Peace and Justice, Princeton University, 2014; Graduate School of Education, University of Pennsylvania, 2014; EITM Summer Institute, Duke University, 2014; Center for Lifespan Psychology, Max Planck Institute for Human Development, 2015; School of Communication Research, University of Amsterdam, 2015; Uppsala University, 2016

4. Short Course on Covariate Balancing Propensity Score – Society for Research on Educational Effectiveness Conference, Washington DC, Spring 2013; Uppsala University, 2016

5. Short Course on Matching Methods for Causal Inference – Institute of Behavioral Science, University of Colorado, Boulder, 2009; Department of Political Science, Duke University, 2013.

6. Lecture on Statistics and Social Sciences – New Jersey Japanese School, 2011, 2016; Kaisei Academy, 2012, 2014; Princeton University Wilson College, 2012; University of Tokyo, 2014

ADAMS_00103

Selected Presentations

1. Distinguished speaker, Harvard College Summer Program for Undergraduates in Data Science, 2021.
2. Keynote speaker, Kansas-Western Missouri Chapter of the American Statistical Association, 2021.
3. Invited plenary panelist, Association for Computing Machinery Conference on Fairness, Accountability, and Transparency (ACM FAccT) 2021.
4. Keynote speaker, Taiwan Political Science Association, 2020.
5. Keynote speaker, Boston Japanese Researchers Forum, Massachusetts Institute of Technology, 2020.
6. Keynote speaker, Causal Mediation Analysis Training Workshop, Mailman School of Public Health, Columbia University, 2020.
7. Keynote speaker, Special Workshop on Evidence-based Policy Making. World Economic Forum, Centre for the Fourth Industrial Revolution, Japan, 2020.
8. Distinguished speaker, Institute for Data, Systems, and Society. Massachusetts Institute of Technology, 2019.
9. Keynote speaker, The Harvard Experimental Political Science Graduate Student Conference, Harvard University, 2019.
10. Invited speaker, Beyond Curve Fitting: Causation, Counterfactuals, and Imagination-based AI. Association for the Advancement of Artificial Intelligence, Spring Symposium, Stanford University, 2019.
11. Inaugural speaker, Causal Inference Seminar, Departments of Biostatistics and Statistics, Boston University, 2019.
12. Keynote speaker, The Second Latin American Political Methodology Meeting, Universidad de los Andes (Department of Political Science), 2018.
13. Keynote speaker, The First Latin American Political Methodology Meeting, Pontifical Catholic University of Chile (Department of Political Science), 2017.
14. Keynote speaker, Workshop on Uncovering Causal Mechanisms, University of Munich (Department of Economics), 2016.
15. Keynote speaker, The National Quality Registry Research Conference, Stockholm, 2016.
16. Keynote speaker, The UK-Causal Inference Meeting, University of Bristol (School of Mathematics), 2015.
17. Keynote speaker, The UP-STAT Conference, the Upstate Chapters of the American Statistical Association, 2015.
18. Keynote speaker, The Winter Conference in Statistics, Swedish Statistical Society and Umeå University (Department of Mathematics and Mathematical Statistics), 2015.

ADAMS_00104

19. Inaugural invited speaker, The International Methods Colloquium, Rice University, 2015.
20. Invited speaker, The International Meeting on Experimental and Behavioral Social Sciences, University of Oxford (Nuffield College), 2014.
21. Keynote speaker, The Annual Conference of Australian Society for Quantitative Political Science, University of Sydney, 2013.
22. Keynote speaker, The Graduate Student Conference on Experiments in Interactive Decision Making, Princeton University. 2008.

Conferences Organized

1. The Asian Political Methodology Meetings (January 2014, 2015, 2016, 2017, 2018; co-organizer)
2. The Experimental Research Workshop (September 2012; co-organizer)
3. The 12th World Meeting of the International Society for Bayesian Analysis (June 2012; a member of the organizing committee)
4. Conference on Causal Inference and the Study of Conflict and State Building (May 2012; organizer)
5. The 28th Annual Society for Political Methodology Summer Meeting (July 2011; host)
6. Conference on New Methodologies and their Applications in Comparative Politics and International Relations (February 2011; co-organizer)

Teaching

Courses Taught at Harvard

1. Stat 286/Gov 2003 Causal Inference (formally Stat 186/Gov 2002): introduction to causal inference
2. Gov 2003 Topics in Quantitative Methodology: causal inference, applied Bayesian statistics, machine learning

Courses Taught at Princeton

1. POL 245 Visualizing Data: exploratory data analysis, graphical statistics, data visualization
2. POL 345 Quantitative Analysis and Politics: a first course in quantitative social science
3. POL 451 Statistical Methods in Political Science: basic probability and statistical theory, their applications in the social sciences
4. POL 502 Mathematics for Political Science: real analysis, linear algebra, calculus
5. POL 571 Quantitative Analysis I: probability theory, statistical theory, linear models
6. POL 572 Quantitative Analysis II: intermediate applied statistics

7. POL 573 Quantitative Analysis III: advanced applied statistics
8. POL 574 Quantitative Analysis IV: advanced applied statistics with various topics including Bayesian statistics and causal inference
9. Reading Courses: basic mathematical probability and statistics, applied bayesian statistics, spatial statistics

Advising

Current Students

1. Soubhik Barari (Government)
2. Adam Breuer (Computer Science and Government). To be Assistant Professor, Department of Government and Department of Computer Science, Dartmouth College
3. Jacob Brown (Government)
4. Ambarish Chattopadhyay (Statistics)
5. Shusei Eshima (Government)
6. Georgina Evans (Government)
7. Dae Woong Ham (Statistics)
8. Christopher T. Kenny (Government)
9. Michael Lingzhe Li (MIT, Operations Research Center)
10. Jialu Li (Government)
11. Cory McCartan (Statistics)
12. Sayumi Miyano (Princeton, Politics)
13. Sun Young Park (Government)
14. Casey Petroff (Political Economy and Government)
15. Averell Schmidt (Kennedy School)
16. Sooahn Shin (Government)
17. Tyler Simko (Government)
18. Soichiro Yamauchi (Government)
19. Yi Zhang (Statistics)

Current Postdocs

1. Eli Ben-Michael
2. Evan Rosenman

Former Students

1. Alexander Tarr (Ph.D. in 2021, Department of Electrical and Computer Engineering, Princeton University; Dissertation Committee Chair)
2. Connor Jerzak (Ph.D. in 2021, Department of Government, Harvard University). Postdoctoral Fellow, Linkoping University. To be Assistant Professor, Department of Government, University of Texas, Austin
3. Shiro Kuriwaki (Ph.D. in 2021, Department of Government, Harvard University). Postdoctoral Fellow, Stanford University. To be Assistant Professor, Department of Political Science, Yale University
4. Erik Wang (Ph.D. in 2020, Department of Politics, Princeton University). Assistant Professor, Department of Political and Social Change, Australian National University
5. Diana Stanescu (Ph.D. in 2020, Department of Politics, Princeton University). Postdoctoral Fellow, Stanford University
6. Nicole Pashley (Ph.D. in 2020, Department of Statistics, Harvard University). Assistant Professor, Department of Statistics, Rutgers University
7. Asya Magazinnik (Ph.D. in 2020, Department of Politics, Princeton University). Assistant Professor, Department of Political Science, Massachusetts Institute of Technology
8. Max Goplerud (Ph.D. in 2020, Department of Government, Harvard University). Assistant Professor, Department of Political Science, University of Pittsburgh
9. Naoki Egami (Ph.D. in 2020, Department of Politics, Princeton University; Dissertation Committee Chair). Assistant Professor, Department of Political Science, Columbia University
10. Brandon de la Cuesta (Ph.D. in 2019, Department of Politics, Princeton University). Postdoctoral Fellow, Center on Global Poverty and Development, Stanford University
11. Yang-Yang Zhou (Ph.D. in 2019, Department of Politics, Princeton University). Assistant Professor, Department of Political Science, University of British Columbia
12. Winston Chou (Ph.D. in 2019, Department of Politics, Princeton University). Senior Data Scientist at Apple
13. Ted Enamorado (Ph.D. in 2019, Department of Politics, Princeton University; Dissertation Committee Chair). Assistant Professor, Department of Political Science, Washington University in St. Louis
14. Benjamin Fifield (Ph.D. in 2018, Department of Politics, Princeton University; Dissertation Committee Chair). Data Scientist, American Civil Liberties Union
15. Tyler Pratt. (Ph.D. in 2018, Department of Politics, Princeton University). Assistant Professor, Department of Political Science, Yale University
16. Romain Ferrali (Ph.D. in 2018, Department of Politics, Princeton University). Assistant Professor, Aix-Marseille School of Economics

ADAMS_00107

17. Julia Morse (Ph.D. in 2017, Woodrow Wilson School, Princeton University). Assistant Professor, Department of Political Science, University of California, Santa Barbara
18. Yuki Shiraito (Ph.D. in 2017, Department of Politics, Princeton University; Dissertation Committee Chair). Assistant Professor, Department of Political Science, University of Michigan
19. Carlos Velasco Rivera (Ph.D. in 2016, Department of Politics, Princeton University). Research Scientist, Facebook
20. Gabriel Lopez Moctezuma (Ph.D. in 2016, Department of Politics, Princeton University). Assistant Professor, Division of the Humanities and Social Sciences, California Institute of Technology
21. Graeme Blair (Ph.D. in 2016, Department of Politics, Princeton University). Assistant Professor, University of California, Los Angeles
22. Jaquilyn R. Waddell Boie (Ph.D. in 2015, Department of Politics, Princeton University). Private consultant
23. Scott Abramson (Ph.D. in 2014, Department of Politics, Princeton University). Associate Professor, Department of Political Science, University of Rochester
24. Michael Barber (Ph.D. in 2014, Department of Politics, Princeton University). Associate Professor, Department of Political Science, Brigham Young University
25. In Song Kim (Ph.D. in 2014, Department of Politics, Princeton University). Associate Professor, Department of Political Science, Massachusetts Institute of Technology
26. Alex Ruder (Ph.D. in 2014, Department of Politics, Princeton University). Senior Community Economic Development Advisor, Federal Reserve Bank of Atlanta
27. Meredith Wilf (Ph.D. in 2014, Department of Politics, Princeton University). Senior Director, Capital Rx
28. Will Bullock. (Ph.D. candidate, Department of Politics, Princeton University). Senior Researcher, Facebook
29. Teppei Yamamoto (Ph.D. in 2011, Department of Politics, Princeton University; Dissertation Committee Chair). Associate Professor, Department of Political Science, Massachusetts Institute of Technology
30. Dustin Tingley (Ph.D. in 2010, Department of Politics, Princeton University). Professor, Department of Government, Harvard University
31. Aaron Strauss (Ph.D. in 2009, Department of Politics, Princeton University). Former Executive Director, Analyst Institute
32. Samir Soneji (Ph.D. in 2008, Office of Population Research, Princeton University; Dissertation Committee Chair). Associate Professor, Department of Health Behavior at the Gillings School of Global Public Health, University of North Carolina, Chapel Hill
33. Ying Lu (Ph.D. in 2005, Woodrow Wilson School, Princeton University; Dissertation Committee Chair). Associate Professor, Steinhardt School of Culture, Education, and Human Development, New York University

ADAMS_00108

Former Predocs and Postdocs

1. Zhichao Jiang (Postdoctoral Fellow, 2016–2019). Assistant Professor, Department of Biostatistics and Epidemiology, School of Public Health and Health Sciences, University of Massachusetts, Amherst
2. Adeline Lo (Postdoctoral Fellow, 2016–2019). Assistant Professor, Department of Political Science, University of Wisconsin, Madison
3. Yunkyu Sohn (Postdoctoral Fellow, 2016–2018). Assistant Professor, School of Political Science and Economics, Waseda University
4. Xiaolin Yang (Postdoctoral Fellow, 2015–2017). Research Scientist, Amazon
5. Santiago Olivella (Postdoctoral Fellow, 2015–2016). Associate Professor, Department of Political Science, University of North Carolina
6. Drew Dimmery (Predoctoral Fellow, 2015–2016). Research Scientist, Facebook
7. James Lo (Postdoctoral Fellow, 2014–2016). Assistant Professor, Department of Political Science, University of Southern California
8. Steven Liao (Predoctoral Fellow, 2014–2015). Assistant Professor, Department of Political Science, University of California, Riverside
9. Michael Higgins (Postdoctoral Fellow, 2013–2015). Associate Professor, Department of Statistics, Kansas State University
10. Kentaro Hirose (Postdoctoral Fellow, 2012–2015). Assistant Professor, Waseda Institute for Advanced Studies
11. Chad Hazlett (Predoctoral Fellow, 2013–2014). Associate Professor, Departments of Political Science and Statistics, University of California, Los Angeles
12. Florian Hollenbach (Predoctoral Fellow, 2013–2014). Associate Professor, Department of International Economics, Government and Business at the Copenhagen Business School
13. Marc Ratkovic (Predoctoral and Postdoctoral Fellow, 2010–2012). Assistant Professor, Department of Politics, Princeton University

Editorial and Referee Service

Co-editor for *Journal of Causal Inference* (2014 – present)

Associate editor for *American Journal of Political Science* (2014 – 2019), *Journal of Business & Economic Statistics* (2015 – 2024), *Journal of Causal Inference* (2011 – 2014), *Journal of Experimental Political Science* (2013 – 2017), *Observational Studies* (2014 – present), *Political Analysis* (2014 – 2017).

Editorial board member for *Asian Journal of Comparative Politics* (2014 – present), *Journal of Educational and Behavioral Statistics* (2011 – present), *Journal of Politics* (2007 – 2008, 2019–2020), *Journal of Research on Educational Effectiveness* (2014 – 2016), *Political Analysis* (2010 – 2013), *Political Science Research and Methods* (2019 – present).

ADAMS_00109

Guest editor for *Political Analysis* virtual issue on causal inference (2011).

Referee for *ACM Computing Surveys*, *American Economic Journal: Applied Economics*, *American Economic Review: Insights*, *American Journal of Epidemiology*, *American Journal of Evaluation*, *American Journal of Political Science*, *American Political Science Review*, *American Politics Research*, *American Sociological Review*, *Annals of Applied Statistics*, *Annals of Statistics*, *Annals of the Institute of Statistical Mathematics*, *Biometrics*, *Biometrika*, *Biostatistics*, *BMC Medical Research Methodology*, *British Journal of Mathematical and Statistical Psychology*, *British Journal of Political Science*, *Canadian Journal of Statistics*, *Chapman & Hall/CRC Press*, *Child Development*, *Communications for Statistical Applications and Methods*, *Computational Statistics and Data Analysis*, *Electoral Studies*, *Econometrica*, *Econometrics*, *Empirical Economics*, *Environmental Management*, *Epidemiology*, *European Union Politics*, *IEEE Transactions on Information Theory*, *International Journal of Biostatistics*, *International Journal of Epidemiology*, *International Journal of Public Opinion Research*, *International Migration Review*, John Wiley & Sons, *Journal of Applied Econometrics*, *Journal of Applied Statistics*, *Journal of Biopharmaceutical Statistics*, *Journal of Business and Economic Statistics*, *Journal of Causal Inference*, *Journal of Computational and Graphical Statistics*, *Journal of Conflict Resolution*, *Journal of Consulting and Clinical Psychology*, *Journal of Econometrics*, *Journal of Educational and Behavioral Statistics*, *Journal of Empirical Legal Studies*, *Journal of Multivariate Analysis*, *Journal of Official Statistics*, *Journal of Peace Research*, *Journal of Politics*, *Journal of Research on Educational Effectiveness*,*Journal of Statistical Planning and Inference*, *Journal of Statistical Software*, *Journal of Survey Statistics and Methodology*, *Journal of the American Statistical Association (Case Studies and Applications; Theory and Methods)*, *Journal of the Japanese and International Economies*, *Journal of the Japan Statistical Society*, *Journal of the Royal Statistical Society (Series A; Series B; Series C)*, *Law & Social Inquiry*, *Legislative Studies Quarterly*, *Management Science*, Multivariate Behavioral Research, National Science Foundation (Economics; Methodology, Measurement, and Statistics; Political Science), Natural Sciences and Engineering Research Council of Canada, *Nature Machine Intelligence*, *NeuroImage*, *Osteoporosis International*, *Oxford Bulletin of Economics and Statistics*, *Pharmaceutical Statistics*, *Pharmacoepidemiology and Drug Safety*, *PLOS One*, *Policy and Internet*, *Political Analysis*, *Political Behavior*, *Political Communication*, *Political Research Quarterly*, *Political Science Research and Methods*, *Population Health Metrics*, *Population Studies*, *Prevention Science*, *Proceedings of the National Academy of Sciences*, Princeton University Press, *Psychological Methods*, *Psychometrika*, *Public Opinion Quarterly*, *Quarterly Journal of Economics*, *Quarterly Journal of Political Science*, *Review of Economics and Statistics*, Routledge, Sage Publications, *Scandinavian Journal of Statistics*, *Science*, Sloan Foundation, Springer, *Sociological Methodology*, *Sociological Methods & Research*, *Statistical Methodology*, *Statistical Methods and Applications*, *Statistical Methods in Medical Research*, *Statistical Science*, *Statistica Sinica*, *Statistics & Probability Letters*, *Statistics in Medicine*, *Systems Biology*, U.S.-Israel Binational Science Foundation, *Value in Health*, *World Politics.*

University and Departmental Committees

Harvard University

Department of Government

ADAMS_00110

Member, Curriculum and Educational Policy Committee (2020–2021)

Member, Second-year Progress Committee (2019–2020)

Member, Graduate Placement Committee (2019–2020)

Member, Graduate Admissions Committee (2018–2019)

Member, Graduate Poster Session Committee (2018–2019)

Department of Statistics

Chair, Senior Faculty Search Committee (2021–2022)

Member, Junior Faculty Search Committee (2018–2019)

Member, Second-year Progress Committee (2018–2019, 2020–2021)

Princeton University

University

Executive Committee Member, Program in Statistics and Machine Learning (2013–2018)

Executive Committee Member, Committee for Statistical Studies (2011-2018)

Member, Organizing Committee, Retreat on Data and Information Science at Princeton (2016)

Member, Council of the Princeton University Community (2015)

Member, Search Committee for the Dean of College (2015)

Member, Committee on the Library and Computing (2013–2016)

Member, Committee on the Fund for Experimental Social Science (2013–2018)

Member, Personally Identifiable Research Data Group (2012–2018)

Member, Research Computing Advisory Group (2013–2018)

Member, Task Force on Statistics and Machine Learning (2014–2015)

Department of Politics

Chair, Department Committee on Research and Computing (2012–2018)

Chair, Formal and Quantitative Methods Junior Search Committee (2012–2013, 2014–2015, 2016–2017)

Chair, Reappointment Committee (2015–2016)

Member, Diversity Initiative Committee (2014–2015)

Member, American Politics Junior Search Committee (2012–2014)

Member, Department Chair's Advisory Committee (2010–2013, 2015–2016)

Member, Department Priority Committee (2012–2013, 2014–2015, 2016–2017)

Member, Formal and Quantitative Methods Curriculum Committee (2005–2006)

Member, Formal and Quantitative Methods Junior Search Committee (2009–2010, 2015–2016)

Member, Formal and Quantitative Methods Postdoc Search Committee (2009–2018)

ADAMS_00111

Member, Graduate Admissions Committee (2012–2013)
Member, Reappointment Committee (2014–2016)
Member, Space Committee (2014–2016)
Member, Undergraduate Curriculum Committee (2014–2015)
Member, Undergraduate Exam Committee (2007–2008)
Member, Undergraduate Thesis Prize Committee (2005–2006, 2008–2011)

Center for Statistics and Machine Learning

Executive Committee Member (2016–2018)
Member, Search Committee (2015–2017)

Services to the Profession

National Academies of Sciences, Engineering, and Medicine

Committee on National Statistics, Division of Behavioral and Social Sciences and Education, Panel on the Review and Evaluation of the 2014 Survey of Income and Program Participation Content and Design (2014–2017)

National Science Foundation

Proposal Review Panel (2020)

The Society for Political Methodology

President (2017–2019)
Vice President and President Elect (2015–2017)
Annual Meeting Committee, Chair (2011)
Career Award Committee (2015–2017)
Program Committee for Annual Meeting (2012), Chair (2011)
Graduate Student Selection Committee for the Annual Meeting (2005), Chair (2011)
Miller Prize Selection Committee (2010–2011)
Statistical Software Award Committee (2009–2010)
Emerging Scholar Award Committee (2013)

American Statistical Association

Journal of Educational and Behavioral Statistics Management Committee (2016 – present)

Others

External Expert, Department of Methodology, London School of Economics and Political Science (2017)

Memberships

American Political Science Association; American Statistical Association; Midwest Political Science Association; The Society for Political Methodology.

ADAMS_00112

Handley Affidavit.pdf

DocVerify ID:	C76B5C72-ECA6-4B6C-BD16-160A4B8F2C08
Created:	December 09, 2021 10:31:35 -8:00
Pages:	1
Remote Notary:	Yes / State: OH

This document is a DocVerify VeriVaulted protected version of the document named above. It was created by a notary or on the behalf of a notary, and it is also a DocVerify E-Sign document, which means this document was created for the purposes of Electronic Signatures and/or Electronic Notary. Tampered or altered documents can be easily verified and validated with the DocVerify veriCheck system. This remote online notarization involved the use of communication technology.

Go to www.docverify.com at any time to verify or validate the authenticity and integrity of this or any other DocVerify VeriVaulted document.

E-Signature Summary

E-Signature 1: Lisa Handley (LH)
December 09, 2021 10:48:23 -8:00 [1191C7F1544F] [71.191.84.32]
lrhandley@aol.com (Principal) (Personally Known)

E-Signature Notary: Theresa M Sabo (TMS)
December 09, 2021 10:48:23 -8:00 [A49D9778307A] [74.142.214.254]
tess.sabo@gmail.com
I, Theresa M Sabo, did witness the participants named above electronically sign this document.

DocVerify documents cannot be altered or tampered with in any way once they are protected by the DocVerify VeriVault System. Best viewed with Adobe Reader or Adobe Acrobat. All visible electronic signatures contained in this document are symbolic representations of the persons signature, and not intended to be an accurate depiction of the persons actual signature as defined by various Acts and/or Laws.

IN THE SUPREME COURT OF OHIO

LEAGUE OF WOMEN VOTERS OF OHIO, et al.,	
Relators	**Case No. 2021-1449**
v.	**Original Action Pursuant to Ohio Const., Art. XIX, Sec. 1(C)(3)**
OHIO REDISTRICTING COMMISSION, et al.,	
Respondents.	

AFFIDAVIT OF LISA HANDLEY

Franklin County
/ss
State of Ohio

Now comes affiant Lisa Handley, having been first duly cautioned and sworn, deposes and states as follows:

1. I am over the age of 18 and fully competent to make this declaration. I have personal knowledge of the statements and facts contained herein.
2. For the purposes of this litigation, I have been asked by counsel for LWV Relators to analyze relevant data and provide my expert opinions.
3. To that end, I have personally prepared the report attached to this affidavit as Exhibit A, and swear to its authenticity and to the faithfulness of the opinions expressed and, to the best of my knowledge, the accuracy of the factual statements made therein.

FURTHER AFFIANT SAYETH NAUGHT.

Executed on 12/09/2021, 2021.

Lisa Handley
Signed on 2021/12/09 10:48:23 -8:00
1191C7F1544F

Lisa Handley

Sworn and subscribed before me this 12/09/2021, 2021.

Signed on 2021/12/09 10:48:23 -8:00
A49D9778307A

Notary Public

NOTARY PUBLIC STATE OF OHIO
Theresa M Sabo
Commission # 2016-RE-619622
Electronic Notary Public
State of Ohio
My Comm Exp. Nov 28, 2026
Notary Stamp 2021/12/09 11:48:23 PST A49D9778307A

Notarial act performed by audio-visual communication

C76B5C72-ECA6-4B6C-BD16-160A4B8F2C08 --- 2021/12/09 10:31:35 -8:00 --- Remote Notary

Exhibit A

Affidavit of Dr. Lisa Handley

PROVIDING BLACK VOTERS WITH AN OPPORTUNITY TO ELECT:
A DISTRICT-SPECIFIC, FUNCTIONAL ANALYSIS OF OHIO VOTING BY RACE

Summary.

1. I was retained by counsel for Relators in this matter to conduct a district-specific, functional analysis of voting patterns by race in Cuyahoga County, where there is a significant Black population and it is possible to draw a majority Black congressional district. My task was to ascertain the Black voting age population ("BVAP") necessary to provide Black voters with an opportunity to elect their candidates of choice based on the participation rates and voting patterns by race in recent elections.[1] This affidavit reports the results of my analysis of voting patterns in Cuyahoga County, including recent congressional elections in the 11th Congressional District.
2. A district-specific, functional analysis is required to determine whether a district is likely to provide minority voters with an opportunity to elect their candidates of choice. There is no single universal or statewide demographic target that can be applied for Black voters to elect their candidates of choice – the population needed to create an "effective minority district" varies by location and depends upon the participation rates and voting patterns of Black and white voters in that specific area.
3. An analysis of voting patterns is required to estimate voter participation rates by race, as well as the level of support from Black and white voters for each of the candidates competing in the examined elections. This information can then be used to calculate the Black population concentration required for the Black voters' preferred candidates to win election to office in a specific district. Drawing districts informed by this percentage avoids creating districts that either fail to provide Black voters with the opportunity to elect their candidates of choice or unnecessarily pack minority voters into districts to reduce the number of minority opportunity districts.
4. In *Ohio APRI v. Householder*, I submitted a report concluding that the previous 11th Congressional District of Ohio would be an effective minority district with 45% Black BVAP. 373 F.Supp.3d 978 (S.D. Ohio, May 3, 2019). As summarized by the court, I

[1] I am being compensated at a rate of $300 per hour.

concluded: "[W]ith a 45% BVAP in District 11, African-American voters would have a realistic opportunity to elect their candidate of choice with a 'comfortable margin.' In fact, even with a BVAP as low as 40%, African-American voters would have elected the Black-preferred candidate in the elections studied. [I] concluded that there is no need to draw a majority African-American District 11 in order to allow African-American voters to elect their candidate of choice there." *Id*. at 1044-46.

5. In this report, I shift the focus of my analysis from residents of the 11th Congressional District to residents of Cuyahoga County more broadly and I update the elections analyzed to include those held since I submitted my 2018 report. My reason for studying voting patterns in Cuyahoga County in its entirety is the recognition that the congressional district boundaries will change – no longer including all of the same voters as the current Congressional District 11 – and Congressional District 11 is likely to be redrawn to fall entirely within Cuyahoga County as a consequence of recent amendments to the Ohio Constitution.[2]
6. The results of this updated analysis of voting patterns in Cuyahoga County are consistent with my previous findings: a majority Black district is not required to provide Black voters with a realistic opportunity to elect candidates of their choice to Congress in this area of Ohio. My estimates of participation rates and voting patterns by race in Cuyahoga County has led me to conclude, on the basis of the most challenging election for a Black-preferred candidate to win in Cuyahoga County that I examined (the 2014 gubernatorial election), a 42% BVAP district would offer Black voters an effective opportunity to elect their preferred candidates to Congress.

Professional Experience.

7. I have over thirty-five years of experience as a voting rights and redistricting expert. I have advised scores of jurisdictions and other clients on minority voting rights and redistricting-related issues. I have served as an expert in dozens of voting rights cases. My clients have included state and local jurisdictions, independent redistricting

[2] The Ohio State Constitution was amended in 2018 to specify that if the general assembly draws the congressional plan, the assembly "shall not unduly split governmental units, giving preference to keeping whole, in the order named, counties, then townships and municipal corporations." Article XIX Section 1.(C)(3)(b) of the Ohio Constitution.

commissions (Arizona, Colorado, Michigan), the U.S. Department of Justice, national civil rights organizations, and such international organizations as the United Nations.

8. I have been actively involved in researching, writing, and teaching on subjects relating to voting rights, including minority representation, electoral system design, and redistricting. I co-authored a book, *Minority Representation and the Quest for Voting Equality* (Cambridge University Press, 1992) and co-edited a volume, *Redistricting in Comparative Perspective* (Oxford University Press, 2008), on these subjects. In addition, my research on these topics has appeared in peer-reviewed journals such as *Journal of Politics*, *Legislative Studies Quarterly*, *American Politics Quarterly*, *Journal of Law and Politics*, and *Law and Policy*, as well as law reviews (e.g., *North Carolina Law Review*) and a number of edited books. I hold a Ph.D. in political science from The George Washington University.
9. I have been a principal of Frontier International Electoral Consulting since co-founding the company in 1998. Frontier IEC specializes in providing electoral assistance in transitional democracies and post-conflict countries. In addition, I am a Visiting Research Academic at Oxford Brookes University in Oxford, United Kingdom. Attached to the end of this report as Appendix B is a copy of my *curriculum vitae*.

Calculating the Black Voting Age Population Needed to Elect Black-Preferred Candidates.

10. The Black voting age population (BVAP) percentage needed to elect Black-preferred candidates is calculated by taking into account the relative participation rates of Black and white Ohioans, as well as the expected level of Black support for the Black-preferred candidates (their "cohesiveness") in an area, and the expected level of white voters' "crossover" voting for the Black-preferred candidates. This requires constructing a database that combines demographic information and election results, then analyzing the data for patterns. These patterns are then used to produce estimates of participation rates and voting patterns by race.
11. **Database.** To analyze voting patterns in Ohio requires a database that combines election returns and population data by race (or registration or turnout by race if this information is available). To build this dataset in this instance, 2016, 2018, and 2020 precinct-level shapefiles were acquired from the Voting and Election Science Team. These shapefiles

were joined to precinct-level election returns from the Ohio Secretary of State's office, which were processed and cleaned by OpenElections. In addition, 2012 and 2014 election returns pro-rated to the 2010 voting district ("VTD") level, were acquired from Bill Cooper, who submitted an expert affidavit in *LWVO v. Ohio Redistricting Commission*, 2021-1193. The 2020 Census Block shapefiles, and total and voting age population by race and ethnicity, were obtained from the Census FTP portal. The election returns data was disaggregated down to the level of the 2020 Census block and, for the 2016, 2018, and 2020 election cycles separately, re-aggregated up to the level of the voting precincts used in those years, accounting for precincts split by congressional districts. For the 2012 and 2014 election cycles, the block-level election results were re-aggregated up to the level of the 2010 VTDs, taking into account splits of VTDs by congressional districts.

12. **Elections Analyzed.** I analyzed all recent statewide Ohio general elections held in 2016, 2018, and 2020 to estimate voting patterns by race in Cuyahoga County. This included contests for U.S. President, U.S. Senate, Governor, Attorney General, Secretary of State, Treasurer, and Auditor. I also examined the 2014 general election contests for Governor and Secretary of State,[3] as well as the 2012 election contests for U.S. President and U.S. Senate. In addition, I analyzed the 2016, 2018, and 2020 general elections for U.S. Congress in District 11.
13. **Primary Elections.** As is usually the case in the United States, there is a two-stage election process in Ohio – a primary election and a general election. Black-preferred candidates must win both elections to gain office. The overwhelming majority of Black voters in Ohio vote in the Democratic primary rather than the Republican primary. As a consequence, it is not possible to estimate Black voting behavior in Republican primaries and, in any case, Black voters' candidates of choice are found in Democratic primaries. In the past ten years, there were two statewide Democratic primaries that included African American candidates: the 2018 Democratic primary for Governor and the 2016 Democratic primary for U.S. Senate. I analyzed both of these elections. (Although both contests included African American candidates, these candidates were not, in fact, the candidates preferred by Black voters.) In addition, I analyzed recent Democratic primaries for Congressional District 11.

[3] Data on the other statewide elections held in 2014 (Attorney General, Treasurer, and Auditor) was not readily available. No minority candidates competed in these three statewide election contests.

There were no contested primaries for the congressional seats in 2016 or 2018, but the district had a primary in 2020. There was also a special Democratic primary held in Congressional District 11 in August 2021 when President Biden appointed the incumbent, Rep. Marcia Fudge, as Secretary of the U.S. Department of Housing and Urban Development.[4]

14. The results of the 2016 elections reported here vary slightly from those in my *Ohio APRI v. Householder* report. There are two reasons for this. First, this analysis incorporates all Cuyahoga County precincts, not simply those precincts that fall within the prior boundaries of Congressional District 11. (Congressional District 11 previously included Summit County precincts – these were included in the analysis for my *Ohio APRI v. Householder* report but are excluded here from the countywide analysis; they are, however, included in the congressional elections analyzed.) Second, my *Ohio APRI v. Householder* report relies on 2010 census data, whereas my analysis in this report uses 2020 census data to determine the demographic composition of the precincts for 2016.
15. **Racial Bloc Voting Analysis.** Direct information on how Black and white voters cast their votes is not available; voters' race is not included in their voter registration in Ohio and the race of the voter is not, of course, obtainable from a ballot. To estimate vote choices by race, I used three standard statistical techniques: homogeneous precinct analysis, ecological regression, and ecological inference.
16. Two of these analytic procedures – homogeneous precinct analysis and ecological regression – were employed by the plaintiffs' expert in *Thornburg v. Gingles*, 478 U.S. 30 (1986), and have the benefit of the Supreme Court's approval in that case, and other courts' approval in most subsequent voting rights cases. The third technique, ecological inference, was developed after the *Gingles* decision, and was designed, in part, to address the issue of out-of-bounds estimates (estimates that exceed 100 percent or are less than zero percent), which can arise in ecological regression analysis. Ecological inference analysis has been introduced and accepted in numerous federal and state court proceedings.

---

[4] The precinct election results for the November 2021 general election have yet to be released by the Secretary of State so I have been unable to analyze the 2021 general election for Congressional District 11.

17. *Homogeneous precinct* ("HP") analysis is the simplest technique: it involves comparing the percentage of votes received by each of the candidates in precincts that are racially homogeneous. The general practice is to label a precinct as homogeneous if at least 90 percent of the voting age population is composed of a single race. In fact, the homogeneous results reported are not estimates – they are the actual precinct results. However, most voters in Ohio do not reside in homogeneous precincts, and voters who reside in homogeneous precincts may not be representative of voters who live in more integrated precincts. For this reason, I refer to these percentages as estimates.
18. The second statistical technique I employed, *ecological regression* ("ER"), uses information from all precincts, not simply the homogeneous ones, to derive estimates of the voting behavior of Black and white Ohioans. If there is a strong linear relationship across precincts between the percentage of Blacks (or whites) and the percentage of votes cast for a given candidate, this relationship can be used to estimate the percentage of Blacks and whites voting for each of the candidates in the election contest being examined.
19. The third technique, *ecological inference* ("EI"), was developed by Professor Gary King. This approach also uses information from all precincts but, unlike ecological regression, it does not rely on an assumption of linearity. Instead, it incorporates maximum likelihood statistics to produce estimates of voting patterns by race. In addition, it utilizes the method of bounds, which uses more of the available information from the precinct returns and provides more information about the voting behavior being estimated.[5] The method of bounds also precludes the estimates from exceeding the possible limits. However, unlike ecological regression, EI does not guarantee that the candidate estimates add to 100 percent of each racial group in the elections examined.
20. In addition, I utilized a more recently developed version of ecological inference which I have labeled "EI RxC" in the summary tables found in Appendix A. EI RxC expands the

[5] The following is an example of how the method of bounds works: if a given precinct has 100 voters, of which 75 are Black and 25 are white, and the Black candidate received 80 votes, then at least 55 of the Black voters voted for the Black candidate and at most all 75 did. (The method of bounds is less useful for calculating estimates for white voters, as anywhere between none of the whites and all of the whites could have voted for the candidate.) These bounds are used when calculating EI estimates but not when using ecological regression.

analysis so that differences in the relative rates of minority and white turnout can be taken into account in deriving the estimates of minority and white support for the candidates.

21. Estimates using all four methodological approaches (homogeneous precinct analysis, ecological regression, and the two approaches to ecological inference) are reported in the summary racial bloc voting tables for Cuyahoga County found in Appendix A.

22. **Equalizing Black and white turnout.** Because Black Ohioans who are eligible to vote often turn out to vote at lower rates than white Ohioans (this is consistently the case in Cuyahoga County in recent elections, as indicated by the summary table of voting patterns found in Appendix A), the BVAP needed to ensure that Black voters comprise at least half of the voters in an election is often higher than 50 percent. Once I estimated the respective turnout rates of Black and white voters using the statistical techniques described above, I could mathematically calculate the percentage needed to equalize minority and white voters.[6] But equalizing turnout is only the first step in the process – it does not take into account the voting patterns of Black and white voters. If voting is

---

[6] The equalizing percentage is calculated mathematically by solving the following equation:

Let

M	=	the proportion of the district's voting age population that is Black
W = 1-M	=	the proportion of the district's voting age population that is white
A	=	the proportion of the Black voting age population that turned out to vote
B	=	the proportion of the white voting age population that turned out to vote

Therefore,

M(A)	=	the proportion of the population that is Black and turned out to vote (1)
(1-M)B	=	the proportion of total population that is white and turned out to vote (2)

To find the value of M that is needed for (1) and (2) to be equal, (1) and (2) are set as equal and we solve for M algebraically:

$$
\begin{aligned}
M(A) &= (1 - M)\,B \\
M(A) &= B - M(B) \\
M(A) + M(B) &= B \\
M\,(A + B) &= B \\
M &= B/\,(A+B)
\end{aligned}
$$

Thus, for example, if 39.3% of the black population turned out and 48.3% of the white population turned out, B= .483 and A = .393, and M = .483/ (.393+.483) = .483/.876 = .5513, therefore a black VAP of 55.1% would produce an equal number of black and white voters. (For a more in-depth discussion of equalizing turnout see Kimball Brace, Bernard Grofman, Lisa Handley and Richard Niemi, "Minority Voting Equality: The 65 Percent Rule in Theory and Practice," *Law and Policy*, 10 (1), January 1988.)

racially polarized but a significant number of white voters typically "crossover" to vote for Black voters' preferred candidate, it may be that white crossover voting can compensate for depressed Black turnout relative to white turnout. If this is the case, Black voters need not make up at least 50 percent of the voters in an election for the Black-preferred candidate to win.

23. **Incorporating Minority Cohesion and White Crossover Voting.** Even if Black voters are turning out at lower rates than whites, and voting is racially polarized, if a relatively consistent percentage of white voters support Black-preferred candidates, these candidates can be elected despite the lower Black turnout. This is especially true if Black voters are very cohesive in supporting their preferred candidates. A district-specific, functional analysis should take into account not only differences in the turnout rates of Black and white voters, but also voting patterns by race.[7]

24. To illustrate this mathematically, consider a district that has 1000 persons of voting age, 50% of who are Black and 50% of who are white. Let us begin by assuming that Black turnout is lower than white turnout in a two-candidate general election. In our hypothetical election example, 42% of the Black voting age population (VAP) turn out to vote and 60% of the white VAP vote. This means that, for our illustrative election, there are 210 Black voters and 300 white voters. Further suppose that 96% of the Black voters supported their candidate of choice and 25% of the white voters cast their votes for this candidate (with the other 75% supporting her opponent in the election contest). Thus, in our example, Black voters cast 200 of their 210 votes for the Black-preferred candidate and their other 8 votes for her opponent; white voters cast 75 of their 300 votes for the Black-preferred candidate and 225 votes for their preferred candidate:

[7] For an in-depth discussion of this approach to creating effective minority districts, see Bernard Grofman, Lisa Handley and David Lublin, "Drawing Effective Minority Districts: A Conceptual Framework and Some Empirical Evidence," *North Carolina Law Review*, volume 79 (5), June 2001.

	VAP	turnout	voters	support for Black-preferred candidate	votes for Black-preferred candidate	support for white-preferred candidate	votes for white-preferred candidate
Black	500	0.42	210	0.96	202	0.04	8
White	500	0.60	300	0.25	75	0.75	225
			510		277		233

The candidate of choice of Black voters would receive a total of 277 votes (202 from Black voters and 75 from white voters), while the candidate preferred by white voters would receive only 233 votes (8 from Black voters and 225 from white voters). The Black-preferred candidate would win the election with 55.4% (277/500) of the vote in this hypothetical 50% Black VAP district. And the Black-preferred candidate would be successful despite the fact that the election was racially polarized and that Blacks turned out to vote at a lower rate than whites.

25. The candidate of choice of Black voters would still win the election by a very small margin (50.9%) in a district that is 45% Black with these same voting patterns:

	VAP	turnout	voters	support for Black-preferred candidate	votes for Black-preferred candidate	support for white-preferred candidate	votes for white-preferred candidate
Black	450	0.42	189	0.96	181	0.04	8
White	550	0.60	330	0.25	83	0.75	248
			519		264		255

In a district with a 40% BVAP, however, the Black-preferred candidate would garner only 47.5% of the vote.

Cuyahoga County and Congressional District 11

26. Table 1, below, incorporates the estimates of turnout and votes by race reported in the summary table for Cuyahoga County found in Appendix A,[8] and calculates the percentage of the vote the candidate preferred by Black voters would receive in a district with a given BVAP. The BVAP percentages considered are 35, 40, 45, 50, and 55%. Looking down the last few columns of Table 1, it is apparent that the Black-preferred candidate would win all but one of the 13 statewide general election contests considered in a district with a BVAP of 40%. Moreover, the Black-preferred candidate would win the three congressional general election contests in landslides.
27. Only the 2014 Governor's race would require a district with more than a 40% BVAP for the candidate of choice of Black voters to win. More precisely, the percent BVAP needed for the Black-preferred candidate to win the 2014 Governor's race is 41.4%. This is because the white incumbent (John Kasich) received more support from white voters in Cuyahoga County than any other Republican in the elections I examined.
28. In every general election since 2018, the Black-preferred candidate would receive at least 67% of the vote – and as much as 73% (75% in a congressional contest)– in a 40% BVAP district.
29. Primary elections are more challenging for Black-preferred candidates, but only when there are more than two or three candidates competing. For example, in the 2018 Democratic primary for Governor, six candidates ran for the nomination. The 2021 Special Primary for Congressional District 11 drew 13 candidates, although only two received more than 2% of the vote.
30. On the basis of my analysis of voting patterns in statewide elections over the past decade, and an examination of recent congressional contests, I conclude that a district with a 42% BVAP is likely to provide Black voters with a realistic opportunity to elect their candidates of choice in a newly drawn congressional district located within Cuyahoga County. This is because the election contest that proved the most challenging for the candidate of choice of Black voters to win was the 2014 Governor contest and the percent BVAP needed for the Black-preferred candidate to win this election is 41.4%.

---

[8] The EI estimate that controls for differential turnout – labeled "EI RxC" in the summary racial bloc voting results tables in the Appendix – was used to calculate the percent Black VAP needed to win.

31. A congressional district that is less than majority Black provides Black voters with an opportunity to elect their candidates of choice in Cuyahoga County because, although Black voters in the county usually turn out to vote at lower rates than white voters, Black voters are very cohesive in supporting their preferred candidates, and white voters vote for these Black-preferred candidates in sufficient percentages for the candidate of choice of the Black voters to prevail.

Table 1: Percent Black VAP Needed to Win Election in Cuyahoga County and Congressional District 11

Cuyahoga County Percent Black VAP needed to win	race of B-P candidate	turnout rate for office and percent vote for black-preferred candidates: Black votes: votes cast for office	Black votes: B-P	Black votes: all others	White votes: votes cast for office	White votes: B-P	White votes: all others	percent of vote B-P cand would have received if district was 55% black VAP	percent of vote B-P cand would have received if district was 50% black VAP	percent of vote B-P cand would have received if district was 45% black VAP	percent of vote B-P cand would have received if district was 40% black VAP	percent of vote B-P cand would have received if district was 35% black VAP
GENERAL ELECTIONS												
2020 President	W	54.1	97.1	2.9	75.3	53.2	46.8	73.7	71.6	69.5	67.4	65.4
2018 Governor	W	46.2	96.1	3.9	58.2	52.9	47.1	74.2	72.0	69.9	67.9	65.8
2018 Treasurer	AA	45.8	98.1	1.9	56.0	51.9	48.1	75.0	72.7	70.4	68.2	66.0
2018 Attorney General	W	45.5	97.7	2.3	57.2	56.4	43.6	76.8	74.7	72.7	70.7	68.8
2018 Auditor	W	45.2	95.9	4.1	55.9	52.7	47.3	74.2	72.0	69.9	67.8	65.8
2018 Secretary State	W	45.7	96.8	3.2	56.7	54.2	45.8	75.3	73.2	71.1	69.1	67.1
2018 U.S. Senate	W	45.9	98.3	1.7	57.9	60.4	39.6	79.1	77.2	75.3	73.5	71.7
2016 President	W	63.8	97.8	2.2	65.9	47.9	52.1	74.9	72.4	70.0	67.5	65.0
2016 U.S. Senate	W	59.9	93.9	6.1	64.4	36.2	63.8	66.9	64.0	61.1	58.3	55.5
2014 Governor	W	30.4	88.0	12.0	41.2	30.2	69.8	57.6	54.7	52.0	49.3	46.6
2014 Secretary State	AA	32.1	97.8	2.2	40.3	40.7	59.3	68.9	66.0	63.2	60.5	57.8
2012 President	AA	71.6	99.0	1.0	65.7	53.9	46.1	79.7	77.4	75.2	72.9	70.6
2012 U.S. Senate	W	66.3	98.7	1.3	62.6	57.4	42.6	80.7	78.6	76.6	74.5	72.4
DEMOCRATIC PRIMARIES												
2018 Governor	W	17.8	51.0	49.0	15.4	31.4	68.6	42.9	41.9	40.9	39.9	38.9
2016 U.S. Senate	W	30.3	69.2	30.8	16.2	55.8	44.2	65.1	64.5	63.9	63.2	62.5
CONGRESSIONAL DISTRICT 11												
2020 General	AA	53.6	97.4	2.6	71.6	61.2	38.8	78.5	76.7	75.0	73.3	71.6
2018 General	AA	47.2	98.0	2.0	58.7	62.7	37.3	80.2	78.4	76.7	75.0	73.4
2016 General	AA	62.0	98.0	2.0	60.0	53.4	46.6	78.3	76.1	73.8	71.6	69.3
2020 Dem Primary	AA	16.2	93.0	7.0	22.8	88.6	11.4	90.6	90.4	90.2	90.0	89.8
2021 Special Primary	AA	18.0	48.6	51.4	21.8	53.2	46.8	50.9	51.1	51.3	51.6	51.8

Cuyahoga County, Ohio			Estimates for Black Voters				Estimates for White Voters			
	Party	Race	HP	ER	EI 2x2	EI RxC	HP	ER	EI 2x2	EI RxC
General Elections										
2020 General										
U.S. President										
Joseph Biden	D	W/AA*	95.8	100.6	98.4	97.1	50.3	48.9	50.1	53.2
Donald Trump	R	W/W	3.3	-1.6	1.2	1.7	48.8	49.9	48.7	46.0
others			0.9	1.0	1.0	1.2	1.0	1.1	1.2	0.8
votes for office			*57.1*	*50.5*	*54.1*	*54.1*	*79.9*	*73.2*	*75.3*	*75.3*
2018 General										
Governor										
Richard Cordray	D	W/W	94.8	99.7	97.5	96.1	48.9	48.9	49.8	52.9
Mike Dewine	R	W/W	3.6	-1.6	1.2	1.8	48.9	48.3	47.3	45.0
others			1.7	1.9	1.7	2.1	2.2	2.7	2.5	2.1
votes for office			*48.6*	*42.7*	*46.2*	*46.2*	*63.2*	*55.7*	*58.2*	*58.2*
Treasurer										
Rob Richardson	D	AA	97.2	103.0	99.2	98.1	47.6	48.0	49.4	51.9
Robert Sprague	R	W	2.8	-3.0	0.8	1.9	52.4	52.0	50.6	48.1
votes for office			*48.0*	*42.4*	*45.8*	*45.8*	*60.7*	*53.6*	*56.0*	*56.0*
Attorney General										
Steve Dettelbach	D	W	96.2	101.4	98.7	97.7	51.9	52.5	53.8	56.4
Dave Yost	R	W	3.8	-1.4	1.4	2.3	48.1	47.4	46.2	43.6
votes for office			*47.8*	*42.0*	*45.5*	*45.5*	*62.1*	*54.8*	*57.2*	*57.2*
Auditor										
Zack Space	D	W	95.0	100.3	97.7	95.9	48.5	48.5	49.6	52.7
Keith Faber	R	W	2.3	-3.1	0.7	1.4	47.4	46.7	45.2	43.0
Robert Coogan	Lib	W	2.7	2.8	2.5	2.7	4.1	4.8	4.6	4.3
votes for office			*47.3*	*41.8*	*45.2*	*45.2*	*60.6*	*53.5*	*55.9*	*55.9*
Secretary of State										
Kathleen Clyde	D	W	95.8	101.0	98.4	96.8	49.9	50.2	51.2	54.2
Frank LaRose	R	W	3.0	-2.3	0.9	1.6	48.0	47.3	46.0	43.8
Dustin Nanna	Lib	W	1.2	1.3	1.3	1.5	2.1	2.5	2.4	2.0
votes for office			*47.9*	*42.3*	*45.7*	*45.7*	*61.5*	*54.3*	*56.7*	*56.7*

Cuyahoga County, Ohio			Estimates for Black Voters				Estimates for White Voters			
	Party	Race	HP	ER	EI 2x2	EI RxC	HP	ER	EI 2x2	EI RxC
2018 General (cont)										
U.S. Senate										
Sherrod Brown	D	W	97.8	102.6	99.3	98.3	55.9	56.5	57.8	60.4
Jim Renacci	R	W	2.2	-2.7	0.6	1.7	44.1	43.5	42.3	39.6
votes for office			*48.3*	*42.5*	*45.9*	*45.9*	*62.8*	*55.4*	*57.9*	*57.9*
2016 General										
U.S. President										
Hillary Clinton	D	W	97.3	103.0	99.3	97.8	45.9	45.1	46.2	47.9
Donald Trump	R	W	1.7	-9.8	0.6	1.1	50.1	50.2	48.8	47.7
others			1.0	0.8	0.9	1.1	4.1	4.8	4.7	4.4
votes for office			*67.1*	*61.3*	*63.8*	*63.8*	*72.5*	*63.4*	*65.9*	*65.9*
U.S. Senate										
Ted Strickland	D	W	91.6	97.5	95.0	93.9	35.1	33.9	34.2	36.2
Rob Portman	R	W	4.6	-1.8	1.5	1.7	60.4	60.7	60.0	59.1
others			3.8	4.3	4.0	4.3	4.5	5.4	5.2	4.7
votes for office			*62.9*	*57.2*	*59.9*	*59.9*	*71.1*	*62.1*	*64.4*	*64.4*
2014 General										
Governor										
Edward FitzGerald	D	W	85.1	89.8	88.2	88.0	29.2	29.2	28.4	30.2
Joh Kasich	R	W	14.9	10.2	11.9	12.0	70.8	70.8	71.7	69.8
votes for office			*31.3*	*27.4*	*30.4*	*30.4*	*42.8*	*37.9*	*41.2*	*41.2*
Secretary of State										
Nina Turner	D	AA	97.2	103.2	98.8	97.8	38.1	38.9	39.2	40.7
Jon Husted	R	W	2.8	-3.2	1.3	2.2	61.9	61.0	60.8	59.3
votes for office			*32.5*	*29.0*	*32.1*	*32.1*	*41.6*	*36.9*	*40.3*	*40.3*
2012 General										
U.S. President										
Barack Obama	D	AA	99.1	104.5	99.4	99.0	51.6	53.3	54.6	53.9
Mitt Romney	R	W	0.9	-4.5	0.4	1.0	48.4	46.7	45.4	46.1
votes for office			*73.2*	*69.7*	*71.6*	*71.6*	*70.2*	*64.3*	*65.7*	*65.7*

Cuyahoga County, Ohio			Estimates for Black Voters				Estimates for White Voters			
	Party	Race	HP	ER	EI 2x2	EI RxC	HP	ER	EI 2x2	EI RxC
2012 General (cont)										
U.S. Senate										
Sherrod Brown	D	W	98.2	103.1	99.4	98.7	55.2	56.6	57.4	57.4
Josh Mandel	R	W	1.8	-3.2	0.6	1.3	44.8	43.4	42.6	42.6
votes for office			*67.5*	*64.4*	*66.3*	*66.3*	*66.5*	*60.8*	*62.6*	*62.6*
Democratic Primaries										
2018 Primary										
Governor										
Richard Cordray	D	W/W	43.0	39.5	42.0	41.2	58.3	59.5	61.8	60.7
Dennis Kucinich	D	W/AA*	50.5	53.3	51.2	51.0	34.1	33.0	31.5	31.4
Bill O'Neill	D	W/AA*	29.0	3.3	3.1	3.3	1.5	1.3	1.3	1.5
Paul Ray	D	W/W	0.7	0.7	0.7	1.0	0.5	0.5	0.6	0.6
Joe Schiavoni	D	W/W	1.8	1.8	1.8	2.2	5.3	5.5	4.9	5.2
Larry Ealy	D	AA/W	1.2	1.4	1.0	1.3	0.3	0.2	0.4	0.6
votes for office			*17.5*	*14.9*	*17.8*	*17.8*	*14.4*	*12.9*	*15.4*	*15.4*
2016 Primary										
U.S. Senator										
Kelli Prather	D	AA	12.4	13.4	13.0	13.4	10.4	11.5	11.3	10.3
P.G. Sittenfeld	D	W	17.5	15.9	16.4	17.4	31.8	32.1	32.4	33.9
Ted Strickland	D	W	70.1	70.7	70.7	69.2	57.8	56.4	56.3	55.8
votes for office			*29.4*	*27.9*	*30.3*	*30.3*	*16.6*	*14.1*	*16.2*	*16.2*

Congressional District 11				Estimates for Black Voters				Estimates for White Voters			
	Party	Race	Vote	HP	ER	EI 2x2	EI RxC	HP	ER	EI 2x2	EI RxC
2016 General											
Marcia Fudge	D	AA	80.3	96.4	100.4	98.6	98.0	42.0	51.5	53.7	53.4
Beverly Goldstein	R	W	19.8	3.6	-0.4	1.4	2.0	58.0	48.5	46.3	46.6
votes for office				*62.8*	*58.9*	*62.0*		*69.6*	*57.6*	*60.0*	
2018 General											
Marcia Fudge	D	AA	82.2	97.5	100.6	99.2	98.0	46.7	57.5	59.4	62.7
Beverly Goldstein	R	W	17.8	2.5	-0.6	0.7	2.0	53.4	42.5	40.6	37.3
votes for office				*48.4*	*43.7*	*47.2*		*64.8*	*55.5*	*58.7*	
2020 General											
Marcia Fudge	D	AA	80.1	95.5	98.9	97.6	97.4	44.7	55.5	57.4	61.2
Laverne Gore	R	AA	20	4.5	1.1	2.4	2.6	55.3	44.6	3.6	38.8
votes for office				*54.9*	*49.8*	*53.6*		*78.5*	*70.0*	*71.6*	
2020 Democratic Primary											
Marcia Fudge	D	AA	90.5	93.1	92.6	93.9	93.0	87.2	85.3	86.7	88.6
Others	D		9.5	6.9	7.3	6.1	7.0	12.8	14.7	13.2	11.4
votes for office				*16.7*	*13.4*	*16.2*		*15.9*	*17.4*	*22.8*	
2021 Special Primary											
Shontel Brown	D	AA	50.1	49.3	48.0	49.6	48.6	52.9	49.7	52.1	53.2
Nina Turner	D	AA	44.6	44.7	45.8	44.5	45.3	37.1	44.4	43.3	41.9
Others	D		5.3	6.0	6.1	5.7	6.1	10.0	5.8	4.6	4.9
Turnout/VAP				*18.4*	*15.1*	*18.0*		*11.8*	*14.6*	*21.8*	
2021 Special General											
Shontel Brown	D	AA	78.8								
Laverne Gore	R	AA	21.2								
votes for office											

Lisa R. Handley
CURRICULUM VITAE

Professional Experience

Dr. Handley has over thirty years of experience in the areas of redistricting and voting rights, both as a practitioner and an academician, and is recognized nationally and internationally as an expert on these subjects. She has advised numerous clients on redistricting and has served as an expert in dozens of redistricting and voting rights court cases. Her clients have included the U.S. Department of Justice, civil rights organizations, independent redistricting commissions and scores of state and local jurisdictions. Internationally, Dr. Handley has provided electoral assistance in more than a dozen countries, serving as a consultant on electoral system design and redistricting for the United Nations, UNDP, IFES, and International IDEA. In addition, Dr. Handley served as Chairman of the Electoral Boundaries Commission in the Cayman Islands.

Dr. Handley has been actively involved in research, writing and teaching on the subjects of redistricting and voting rights. She has co-written a book, Minority Representation and the Quest for Voting Equality (Cambridge University Press, 1992) and co-edited a volume (Redistricting in Comparative Perspective, Oxford University Press, 2008) on these subjects. Her research has also appeared in peer-reviewed journals such as *Journal of Politics*, *Legislative Studies Quarterly*, *American Politics Quarterly*, *Journal of Law and Politics*, and *Law and Policy,* as well as law reviews and edited books. She has taught political science undergraduate and graduate courses related to these subjects at several universities including the University of Virginia and George Washington University. Dr. Handley is a Visiting Research Academic at Oxford Brookes University in the United Kingdom.

Dr. Handley is the President of Frontier International Consulting, a consulting firm that specializes in providing electoral assistance in transitional and post-conflict democracies. She also works as an independent election consultant both in the United States and internationally.

Education

Ph.D. The George Washington University, Political Science, 1991

Present Employment

President, Frontier International Electoral Consulting LLC (since co-founding company in 1998).

Senior International Electoral Consultant Technical assistance for clients such as the UN, UNDP and IFES on electoral system design and boundary delimitation

Visiting Research Academic, Centre for Development and Emergency Practice (CENDEP), Oxford Brookes University

U.S. Clients since 2000

American Civil Liberties Union (expert testimony in Ohio partisan gerrymander challenge and challenge to Commerce Department inclusion of citizenship question on 2020 census form)

Lawyers Committee for Civil Rights Under Law (expert testimony in challenges to statewide judicial elections in Texas and Alabama)

US Department of Justice (expert witness testimony in several Section 2 and Section 5 cases)

Alaska: Alaska Redistricting Board (redistricting consultation, expert witness testimony)

Arizona: Arizona Independent Redistricting Board (redistricting consultation, expert witness)

Arkansas: expert witness for Plaintiffs in Jeffers v. Beebe

Colorado: Colorado Redistricting Board (redistricting consultation)

Connecticut: State Senate and State House of Representatives (redistricting consultation)

Florida: State Senate (redistricting consultation)

Kansas: State Senate and House Legislative Services (redistricting consultation)

Louisiana: Louisiana Legislative Black Caucus (expert witness testimony)

Massachusetts: State Senate (redistricting consultation)

Maryland: Attorney General (redistricting consultation, expert witness testimony)

Miami-Dade County, Florida: County Attorney (redistricting consultation)

Nassau County, New York: Redistricting Commission (redistricting consulting)

New Mexico: State House (redistricting consultation, expert witness testimony)

New York: State Assembly (redistricting consultation)

New York City: Redistricting Commission and Charter Commission (redistricting consultation and Section 5 submission assistance)

New York State Court: Expert to the Special Master (drew congressional lines for state court)

Ohio: State Democratic Party (redistricting litigation support, expert witness testimony)

Pennsylvania: Senate Democratic Caucus (redistricting consultation)

Rhode Island: State Senate and State House (litigation support, expert witness testimony)

Vermont: Secretary of State (redistricting consultation)

International Clients since 2000

United Nations

- Afghanistan – electoral system design and district delimitation expert
- Bangladesh (UNDP) – redistricting expert
- Sierra Leone (UNDP) – redistricting expert
- Liberia (UNMIL, UN peacekeeping mission) – redistricting expert
- Democratic Republic of the Congo (MONUC, UN peacekeeping mission) – election feasibility mission, electoral system design and redistricting expert
- Kenya (UN) – electoral system design and redistricting expert
- Haiti (UN) – election feasibility mission, electoral system design and redistricting expert
- Zimbabwe (UNDP) – redistricting expert
- Lead Writer on the topic of boundary delimitation (redistricting) for ACE (Joint UN, IFES and IDEA project on the Administration and Cost of Elections Project)

International Foundation for Election Systems (IFES)

- Afghanistan – district delimitation expert
- Sudan – redistricting expert
- Kosovo – electoral system design and redistricting expert
- Nigeria – redistricting expert
- Nepal – redistricting expert
- Georgia – electoral system design and district delimitation expert
- Yemen – redistricting expert
- Lebanon – electoral system design and redistricting expert
- Malaysia – electoral system design and redistricting expert
- Myanmar – electoral system design and redistricting expert
- Ukraine – electoral system design and redistricting expert
- Pakistan – consultant for developing redistricting software
- Principal consultant for the Delimitation Equity Project – conducted research, wrote reference manual and developed training curriculum
- Writer on electoral boundary delimitation (redistricting), Elections Standards Project
- Training – developed training curriculum and conducted training workshops on electoral boundary delimitation (redistricting) in Azerbaijan and Jamaica

International Institute for Democracy and Electoral Assistance (International IDEA):

- Consultant on electoral dispute resolution systems
- Technology consultant on use of GIS for electoral district delimitation
- Training – developed training material and conducted training workshop on electoral boundary delimitation (redistricting) for African election officials (Mauritius)
- Curriculum development – boundary delimitation curriculum for the BRIDGE Project

Other international clients have included The Cayman Islands; the Australian Election Commission; the Boundary Commission of British Columbia, Canada; and the Global Justice Project for Iraq.

Publications

Books*:*

Does Torture Prevention Work? Liverpool University Press, 2016 (served as editor and author, with Richard Carver)

Comparative Redistricting in Perspective, Oxford University Press, 2008 (first editor, with Bernard Grofman).

Delimitation Equity Project: Resource Guide, Center for Transitional and Post-Conflict Governance at IFES and USAID publication, 2006 (lead author).

Minority Representation and the Quest for Voting Equality, Cambridge University Press, 1992 (with Bernard Grofman and Richard Niemi).

Academic Journal Articles*:*

“Drawing Electoral Districts to Promote Minority Representation” Representation, forthcoming, published online DOI:10.1080/00344893.2020.1815076.

"Evaluating national preventive mechanisms: a conceptual model,” Journal of Human Rights Practice, Volume 12 (2), July 2020 (with Richard Carver).

“Minority Success in Non-Majority Minority Districts: Finding the ‘Sweet Spot’,” Journal of Race, Ethnicity and Politics, forthcoming (with David Lublin, Thomas Brunell and Bernard Grofman).

”Has the Voting Rights Act Outlived its Usefulness: In a Word, “No,” Legislative Studies Quarterly, volume 34 (4), November 2009 (with David Lublin, Thomas Brunell and Bernard Grofman).

“Delimitation Consulting in the US and Elsewhere,” Zeitschrift für Politikberatung, volume 1 (3/4), 2008 (with Peter Schrott).

“Drawing Effective Minority Districts: A Conceptual Framework and Some Empirical Evidence,” North Carolina Law Review, volume 79 (5), June 2001 (with Bernard Grofman and David Lublin).

“A Guide to 2000 Redistricting Tools and Technology” in The Real Y2K Problem: Census 2000 Data and Redistricting Technology, edited by Nathaniel Persily, New York: Brennan Center, 2000.

"1990s Issues in Voting Rights," Mississippi Law Journal, 65 (2), Winter 1995 (with Bernard Grofman).

"Minority Turnout and the Creation of Majority-Minority Districts," American Politics Quarterly, 23 (2), April 1995 (with Kimball Brace, Richard Niemi and Harold Stanley).

"Identifying and Remedying Racial Gerrymandering," Journal of Law and Politics, 8 (2), Winter 1992 (with Bernard Grofman).

"The Impact of the Voting Rights Act on Minority Representation in Southern State Legislatures," Legislative Studies Quarterly, 16 (1), February 1991 (with Bernard Grofman).

"Minority Population Proportion and Black and Hispanic Congressional Success in the 1970s and 1980s," American Politics Quarterly, 17 (4), October 1989 (with Bernard Grofman).

"Black Representation: Making Sense of Electoral Geography at Different Levels of Government," Legislative Studies Quarterly, 14 (2), May 1989 (with Bernard Grofman).

"Minority Voting Equality: The 65 Percent Rule in Theory and Practice," Law and Policy, 10 (1), January 1988 (with Kimball Brace, Bernard Grofman and Richard Niemi).

"Does Redistricting Aimed to Help Blacks Necessarily Help Republicans?" Journal of Politics, 49 (1), February 1987 (with Kimball Brace and Bernard Grofman).

Chapters in Edited Volumes:

"Effective torture prevention," Research Handbook on Torture, Sir Malcolm Evans and Jens Modvig (eds), Cheltenham: Edward Elgar, 2020 (with Richard Carver).

"Redistricting" in Oxford Handbook of Electoral Systems, Erik Herron Robert Pekkanen and Matthew Shugart (eds), Oxford: Oxford University Press, 2018.

"Role of the Courts in the Electoral Boundary Delimitation Process," in International Election Remedies, John Hardin Young (ed.), Chicago: American Bar Association Press, 2017.

"One Person, One Vote, Different Values: Comparing Delimitation Practices in India, Canada, the United Kingdom, and the United States," in Fixing Electoral Boundaries in India, edited by Mohd. Sanjeer Alam and K.C. Sivaramakrishman, New Delhi: Oxford University Press, 2015.

"Delimiting Electoral Boundaries in Post-Conflict Settings," in Comparative Redistricting in Perspective, edited by Lisa Handley and Bernard Grofman, Oxford: Oxford University Press, 2008.

"A Comparative Survey of Structures and Criteria for Boundary Delimitation," in Comparative Redistricting in Perspective, edited by Lisa Handley and Bernard Grofman, Oxford: Oxford University Press, 2008.

"Drawing Effective Minority Districts: A Conceptual Model," in Voting Rights and Minority Representation, edited by David Bositis, published by the Joint Center for Political and Economic Studies, Washington DC, and University Press of America, New York, 2006.

"Electing Minority-Preferred Candidates to Legislative Office: The Relationship Between Minority Percentages in Districts and the Election of Minority-Preferred Candidates," in Race and Redistricting in the 1990s, edited by Bernard Grofman; New York: Agathon Press, 1998 (with Bernard Grofman and Wayne Arden).

"Estimating the Impact of Voting-Rights-Related Districting on Democratic Strength in the U.S. House of Representatives," in Race and Redistricting in the 1990s, edited by Bernard Grofman; New York: Agathon Press, 1998 (with Bernard Grofman).

"Voting Rights in the 1990s: An Overview," in Race and Redistricting in the 1990s, edited by Bernard Grofman; New York: Agathon Press, 1998 (with Bernard Grofman and Wayne Arden).

"Racial Context, the 1968 Wallace Vote and Southern Presidential Dealignment: Evidence from North Carolina and Elsewhere," in Spatial and Contextual Models in Political Research, edited by Munroe Eagles; Taylor and Francis Publishing Co., 1995 (with Bernard Grofman).

"The Impact of the Voting Rights Act on Minority Representation: Black Officeholding in Southern State Legislatures and Congressional Delegations," in The Quiet Revolution: The Impact of the Voting Rights Act in the South, 1965-1990, eds. Chandler Davidson and Bernard Grofman, Princeton University Press, 1994 (with Bernard Grofman).

"Preconditions for Black and Hispanic Congressional Success," in United States Electoral Systems: Their Impact on Women and Minorities, eds. Wilma Rule and Joseph Zimmerman, Greenwood Press, 1992 (with Bernard Grofman).

Electronic Publication:

"Boundary Delimitation" Topic Area for the Administration and Cost of Elections (ACE) Project, 1998. Published by the ACE Project on the ACE website (www.aceproject.org).

Additional Writings of Note:

Amicus brief presented to the US Supreme Court in Gill v. Whitford, Brief of Political Science Professors as Amici Curiae, 2017 (one of many social scientists to sign brief)

Amicus brief presented to the US Supreme Court in Shelby County v. Holder, Brief of Historians and Social Scientists as Amici Curiae, 2013 (one of several dozen historians and social scientists to sign brief)

Amicus brief presented to the US Supreme Court in Bartlett v. Strickland, 2008 (with Nathaniel Persily, Bernard Grofman, Bruce Cain, and Theodore Arrington).

Recent Court Cases

In the past ten years, Dr. Handley has served as an testifying expert or expert consultant in the following cases:

Ohio Philip Randolph Institute v. Larry Householder (2019) – partisan gerrymander challenge to Ohio congressional districts; testifying expert for ACLU on minority voting patterns

State of New York v. U.S. Department of Commerce/ New York Immigration Coalition v. U.S. Department of Commerce (2018-2019) – challenge to inclusion of citizenship question on 2020 census form; testifying expert on behalf of ACLU

U.S. v. City of Eastpointe (settled 2019) – minority vote dilution challenge to City of Eastpointe, Michigan, at-large city council election system; testifying expert on behalf of U.S. Department of Justice

Alabama NAACP v. State of Alabama (decided 2020) – minority vote dilution challenge to Alabama statewide judicial election system; testifying expert on behalf of Lawyers Committee for Civil Rights Under Law

Lopez v. Abbott (2017-2018) – minority vote dilution challenge to Texas statewide judicial election system; testifying expert on behalf of Lawyers Committee for Civil Rights Under Law

Personhuballuah v. Alcorn (2015-2017) – racial gerrymandering challenge to Virginia congressional districts; expert for the Attorney General and Governor of the State of Virginia; written testimony on behalf of Governor

Perry v. Perez (2014) – Texas congressional and state house districts (Section 2 case before federal court in San Antonio, Texas; testifying expert for the U.S. Department of Justice)

Jeffers v. Beebe (2012) – Arkansas state house districts (testifying expert for the Plaintiffs)

State of Texas v. U.S. (2011-2012) – Texas congressional and state house districts (Section 5 case before the Circuit Court of the District of Columbia; testifying expert for the U.S. Department of Justice)

In RE 2011 Redistricting Cases (2011-2012) – State legislative districts for State of Alaska (testifying expert for the Alaska Redistricting Board)

Contact Information

Email: lrhandley@aol.com; lrhandley.Frontier@gmail.com
Telephone: ++1.301.765.5024

IN THE SUPREME COURT OF OHIO

League of Women Voters of Ohio, et al., *Relators*, **v.** **Governor Michael DeWine, et al.** *Respondents.*	Case No. 2021-1449 Original Action Filed Pursuant to Ohio Const., art. XIX Apportionment Case

AFFIDAVIT OF CONGRESSWOMAN MARCY KAPTUR

STATE OF OHIO)
) SS:
COUNTY OF LUCAS)

Now comes affiant Marcy Kaptur, having been first duly cautioned and sworn, deposes and states as follows:

1. I am over the age of 18 and fully competent to offer the testimony contained herein. I make these statements based on my personal knowledge.
2. I am a member of the United States House of Representatives, representing Ohio's 9th congressional district. I was first elected to Congress in November of 1982, and was sworn in on January 3, 1982. I have represented the 9th congressional district continuously since then.
3. I am a member of the Democratic Party.
4. As it is drawn under the current congressional map, which was enacted in 2011 (the "2011 Map"), Ohio's 9th congressional district is a long, slender district that stretches from Toledo to Cleveland. It includes portions of Cuyahoga, Erie, Lorain, Lucas, and Ottawa counties. It's been infamously described as the "Snake on the Lake."

5. Under the 2011 Map, the neighboring 5th congressional district lies primarily to the west and southwest of the 9th congressional district. The 5th district is roughly square-shaped, and encompasses the northwestern corner of Ohio.

6. I had no input into the 2011 Map. When I first saw it, I was immediately concerned about how the 9th congressional district was drawn. Among other things, it divides up communities and counties, so that the district encompasses only small portions of several counties, from Cuyahoga County to Lucas County. The district is very long and slender, and not compact.

7. I found it astonishing and very troubling that the district was drawn in that manner. It is important to draw compact congressional districts that preserve communities. It is much harder to build communities when their congressional representation is divided.

8. I also had no input into the Ohio congressional district map that Governor DeWine signed into law on November 20, 2021 (the "2021 Map"), but I reviewed it after it became publicly available.

9. Unfortunately, many of the aspects of the 2011 Map that concerned me are not remedied in the 2021 Map, but are actually exacerbated.

10. For example, the 5th congressional district under the 2021 Map would be even longer and more spread out than the "Snake on the Lake," the 9th district under the 2011 Map. It is not compact. It includes Lorain County, which is just west of Cleveland in the northeast quadrant of Ohio, and stretches all the way to the western border of the state, where it curves south and covers Paulding, Van Wert, and Mercer Counties, all of which are along the Indiana border.

11. The 2021 Map also separates the cities of Toledo and Lorain, placing the former in the 9th district, and the latter in the 5th district.

12. I am well familiar with Lorain and the community around it, as it currently lies within the district that I represent. I have approximately ten years of experience representing that community. It shares more in common with the Toledo community than with more rural areas like Paulding, Van Wert, and Mercer Counties. For example, Lorain and Toledo both lie along the lakefront, which in my experience means that they share common political interests, especially relating to environmental concerns. They also share similar demographic characteristics, including significant minority populations.

13. The people of Lorain and Toledo would not be well served by being combined into an even longer, more spread-out district than they are currently in, or being combined together with distant rural areas near Indiana. Unfortunately, that is exactly what the 2021 Map does.

14. While removing Lorain from the 9th district, the 2021 Map also removes Williams, Fulton, Defiance, and Henry Counties from the 5th district and places them in the 9th district. This exchange serves only to make the 5th district less compact, and to dilute the voting power of both the Lorain and Toledo communities.

FURTHER AFFIANT SAYETH NAUGHT.

Executed on December 6, 2021.

Congresswoman Marcy Kaptur

Congresswoman Marcy Kaptur

Sworn and subscribed before me this 6th day of December, 2021.

Margaret Ryan

Notary Public

My commission expires

NOTARIAL SEAL

STATE OF OHIO

MARGARET J. RYAN
NOTARY PUBLIC - OHIO
MY COMMISSION EXPIRES 11-14-2022

ADAMS_00140