

Exhibit A

**IN THE UNITED STATES DISTRICT COURT
FOR THE MIDDLE DISTRICT OF FLORIDA
TAMPA DIVISION**

UNIVERSITY OF SOUTH FLORIDA COL-
LEGE REPUBLICANS, *et al.*,

Plaintiffs,

v.

HOWARD W. LUTNICK, *et al.*,

Defendants.

Case No. 8:25-cv-02486

**DECLARATION OF DR. CORY MCCARTAN
December 19, 2025**

I, Cory McCartan am over the age of eighteen and am fully competent to make this declaration. I have personal knowledge of the facts stated herein and declare the following to be true and correct:

I. INTRODUCTION AND SCOPE OF WORK

1. My name is Cory McCartan, Ph.D., and I am an Assistant Professor of Statistics and a faculty affiliate in Political Science at the Pennsylvania State University. I specialize in the development and application of statistical methodology in the social sciences.

2. I have been retained by counsel representing the Intervenor-Defendants to evaluate the use of differential privacy methods (DP) and group quarters imputation (GQI) by the Census Bureau (Bureau).

II. SUMMARY OF OPINIONS

3. As a statistical matter, neither DP nor GQI constitute statistical sampling under the definition of that term that the U.S. Supreme Court adopted in *Utah v. Evans*, 536 U.S. 452 (2002).

4. The Bureau's Disclosure Avoidance System (DAS), which uses DP, could not have affected congressional apportionment, because it did not alter the total population count for any state.

5. The Bureau's use of GQI did not affect the apportionment of congressional districts to Florida, or to any other state. Even if all affected group quarters had instead been enumerated as having zero population, congressional apportionment would not change for any state in the nation.

6. The effect of DP and GQI on the population of any particular district in Florida cannot be determined based on publicly available information, but any such effects are likely to be small in magnitude relative to total district populations.

III. QUALIFICATIONS AND EXPERIENCE

7. I have a B.A. in mathematics from Grinnell College (2019) and an M.A. (2021) and Ph.D. (2023) from Harvard University in statistics. My research focuses on developing and applying statistical methodology to problems in the social sciences. In several research projects since 2020, I have studied the effect of differential privacy on the 2020 decennial census and on decennial redistricting.

8. One such project, whose findings were published in the peer-reviewed journal *Science Advances*, was titled "The Use of Differential Privacy for Census Data and Its Impact on Redistricting: the Case of the 2020 U.S. Census" and examined the impact of differential privacy on

redistricting based on preliminary test data produced by the Bureau leading up to the 2020 Census data release.¹² A later project, “Evaluating Bias and Noise Induced by the U.S. Census Bureau’s Privacy Protection Methods,” additionally relied on raw differential privacy output from the Bureau and quantified the effect of differential privacy at different levels of geography.³

9. As part of this research, I have had to be familiar with the details of the decennial census process, including understanding how imputation methods fit into the process of producing final census counts, and how apportionment totals are used to determine the number of congressional districts allocated to each state.

10. I have previously submitted an expert report or testified in seven cases involving redistricting. These cases are listed in my curriculum vitae, a copy of which is attached as Exhibit A. It also includes a complete listing of my publications. For my work in this case, I am being compensated at a rate of \$400.00 per hour. My compensation does not depend in any way on the outcome of the case or on the opinions or testimony that I provide.

IV. DP AND GQI ARE NOT STATISTICAL SAMPLING

A. DP Overview

11. Differential privacy (DP) is a mathematical framework that attempts to formally quantify how private a publication of data is.⁴ This formalization—one particular translation of the notion of privacy into mathematical language—was originally developed in 2006. A system

¹Christopher T. Kenny et al., “The Use of Differential Privacy for Census Data and Its Impact on Redistricting: The Case of the 2020 US Census,” *Science Advances* 7, no. 41 (2021): eabk3283.

²This preliminary test data used different settings that introduced more error into census counts, among other differences. Consequently, the specific numerical findings in the main section of that paper do not apply to the final 2020 census data released by the Bureau.

³Christopher T. Kenny et al., “Evaluating Bias and Noise Induced by the US Census Bureau’s Privacy Protection Methods,” *Science Advances* 10, no. 18 (2024): eadl2524.

⁴Specifically, DP relates a specific mathematical definition of an “edit” to a dataset, and a specific mathematical definition of “information” that can be gained by an attacker, through a mathematical equation.

for altering raw data to satisfy DP is called a differentially private mechanism. Colloquially, such systems may be referred to as “DP” themselves, even though DP is a definition or property rather than a procedure.

12. A critical part of DP is a so-called privacy-loss budget. There is no way to guarantee with certainty that a person’s data could never be reconstructed from published census statistics. Instead, a system with DP guarantees limits the likelihood of a disclosure, according to the privacy-loss budget. A higher budget allows for more accurate data, but also a higher risk of disclosure.

13. The Bureau has withheld decennial census data for privacy reasons since the 1930s.⁵ Beginning in 1990, the Bureau began using more complex techniques to preserve privacy while maximizing the amount of detailed census data that could be released. The Bureau developed a data *swapping* method, where certain household records in one location were swapped with households in another location randomly. At the time this method was developed, the DP formalization had not yet been invented.

14. For the 2020 Census, the Bureau desired a privacy-protection system that provided more formal guarantees, i.e., guarantees about privacy in the language of DP that could be proved to hold mathematically. The Bureau developed a new Disclosure Avoidance System (DAS)—a specific procedure for translating raw census data into privacy-protected summary statistics to be published—designed from the ground up to satisfy DP guarantees (i.e., be a differentially private mechanism).

15. Following the 2020 Census, researchers also showed that the swapping method used

⁵See <https://www2.census.gov/library/visualizations/2019/communications/history-privacy-protection.pdf>.

from 1990-2010 could also be considered to be differentially private in a certain way.⁶

16. While the DAS is quite complex overall—its implementation uses around 340,000 lines of computer code—at its core, it involves two steps:⁷

- a. First, random noise is added to all of the census statistics at different levels of geography. For example, the reported count of the number of Hispanic persons living in block 120570051011055 (the location of the federal courthouse in Tampa) might be adjusted randomly upwards by 8 voters, while the reported count of the number of Hispanic persons living in Hillsborough County might be adjusted downwards by 5 voters. The counts for other racial groups, age groups, etc., as well as total population counts, would also be independently adjusted. Importantly, counts were changed by a smaller absolute amount in larger geographies like counties than in smaller geographies like census blocks.
- b. Second, the resulting noisy counts are adjusted in a *post-processing* step to ensure that they satisfy certain constraints. For example, the random noise may have caused some counts to be negative. Equally important, after the adjustments, totals from smaller geographies may not add up to the totals from larger geographies. The post-processing fixes these inconsistencies, using an algorithm the bureau developed called the Top-Down Algorithm (TDA).

17. Not all census statistics were altered by random noise. The Bureau enforced a number of *invariants* and *constraints*, i.e., statistics that were not altered by the DAS at all. One constraint was that if a census block had no households, then its population must be zero. One

⁶James Bailie, Ruobin Gong, and Xiao-Li Meng, “A Refreshment Stirred, Not Shaken (III): Can Swapping Be Differentially Private?” *Data Privacy Protection and the Conduct of Applied Research: Methods, Approaches and Their Consequences*, 2025, Forthcoming.

⁷John M. Abowd et al., “The 2020 Census Disclosure Avoidance System TopDown Algorithm,” *Harvard Data Science Review*, no. Special Issue 2 (2022).

particularly important invariant was that the total population of each state was not altered at all by the DAS.

18. The noise introduced by the DAS is distinct from the undercounting error of the census enumeration itself. This undercounting error is due to the difficulties of contacting every American resident. The Bureau attempts to measure the undercounting error after each census using a sampling-based method, the Post-Enumeration Survey (PES). However, no PES data are used in the published decennial census data—the PES does not affect apportionment. It is used solely as a tool to understand the quality of the census enumeration, including by outside groups, as is done in Plaintiff's Exhibit 20. Based on the (sampling-based) PES, the Bureau estimates that the 2020 Census undercounted Florida's population by 3.48%, or around 750,000 people.⁸ That cannot be explained by GQI, which added only around 16,500 people.

B. GQI Overview

19. Group quarters is a Bureau term for residences other than housing units, including prisons, nursing homes, college dormitories, military barracks, and shelters. Due to the populations involved and the size of some group quarters, the Bureau takes a different approach to counting group quarters than it does counting population living in housing units.

20. When a group quarters facility does not provide the Bureau with complete information needed to enumerate the population in residence at the facility, the Bureau uses GQI methods it has developed to impute correct population counts for the facility. Plaintiff's Exhibit 26.

21. For facilities without complete data, the Bureau applied one of three specific GQI methods, depending on how complete the available data was: ratio imputation, adjusted residual from facility-level total for college housing, and percentile imputation. Plaintiff's Exhibit 26.

⁸See <https://www.census.gov/library/visualizations/interactive/2020-post-enumeration-survey.html>.

22. Ratio imputation and percentile imputation, like other imputation methods employed by statisticians, use data from similar fully-reported group quarters to fill in missing data for a particular facility. Adjusted residual from facility-level total for college housing is specific to college dormitories, and uses data provided by colleges and universities to the National Center for Education Statistics.

23. Each of these methods, which are described in more detail on pp. 13–16 of Plaintiffs’ Exhibit 26, rely on specific mathematical formulas and external data collected by the Bureau. None of the methods involves any randomness or the selection of a sample of units from a larger population of units.

C. Statistical Sampling

24. “Sampling” is a widely-used term in statistics, with several related technical meanings. Traditionally, “sampling” referred primarily to the process of selecting a subset of units from a larger population of units, almost always at random, in order to make inferences about the larger population. In present practice, “sampling” can also be used to refer to the general procedure of generating random numbers or other types of random data according to a particular *probability distribution*. For example, simulating random tosses of a fair coin on a computer could be described as “sampling from a Bernoulli distribution” (a particular kind of probability distribution applicable to binary outcomes like coin tosses).

25. I understand that in *Utah v. Evans*, 536 U.S. 452 (2002), the Supreme Court interpreted the term “sampling” in 13 U.S.C. § 195 to refer to the traditional meaning of sampling as selecting a subset of units in order to make inferences about a larger population. In *Evans*, the Court considered three relevant aspects of sampling: (1) “sampling seeks to extrapolate the features of a large population from a small one”; (2) “sampling seeks to find a subset that will resemble a whole

through the use of artificial, random selection processes”; and (3) “sampling seeks to extrapolate the sample’s relevant population characteristics to the whole population.”

26. The *Evans* majority specifically found that hot-deck imputation methods did not constitute “sampling” in this sense.

D. Conclusions

27. DP methods do not constitute statistical sampling as a statistical matter under the *Evans* definition because they do not involve extrapolating features of a randomly-selected subset to a larger population. While the DAS uses random numbers, randomness is not used to select a *subset* of geographic units, households, or residents. After random noise is applied, the post-processing algorithm (TDA) adjusts all counts, and does not perform any extrapolation from some units to other units.

28. GQI methods do not constitute statistical sampling as a statistical matter under the *Evans* definition because they do not involve any randomness at all, nor do they involve extrapolating features of a subset to a larger population. No part of the GQI procedure involves random selection of units, or any selection of a subset for the purposes of extrapolating to a larger population. Indeed, properties of a larger collection of complete-data group quarters are used to impute a much smaller set of partial-data group quarters. In terms of statistical methodology, the GQI methods used by the Bureau are much closer to hot-deck imputation, which also uses data from complete households or individuals to fill in missing data for incomplete households or individuals.

V. DP COULD NOT AFFECT APPORTIONMENT

29. As discussed above, the Bureau’s DAS was designed to leave unchanged certain *invariant* statistics. Most critically, these included the total population of every state.

30. Thus, the reported population of every state was not altered by the application of DP methods by their very design. Had the Bureau not used the DAS at all, or used the previous privacy-preserving mechanism of swapping, the totals used for apportionment would have been identical to the ones actually published by the Bureau in 2021.

VI. GQI DID NOT AFFECT APPORTIONMENT

31. To evaluate the possible effect of GQI on apportionment, I examined the publicly available information about GQI provided by the Bureau in Plaintiffs' Exhibit 26. Table 12 of the exhibit reports the number of people imputed to group quarters in each state. In total, around 16,500 people were imputed to group quarters in Florida.

32. I subtracted the number of people imputed to group quarters in each state from the apportionment totals used by the Bureau⁹ I then re-ran the apportionment algorithm used to determine congressional seats, the Huntington-Hill method, using these adjusted totals.

33. Congressional apportionment would have remained the same in every state even if GQI had not been used at all and all group quarters with missing data had been recorded as having zero population.

34. As Footnote 1 in Exhibit 26 explains, the GQI totals in that exhibit have been slightly modified and rounded for privacy reasons. However, the rounding appears to be only to the tens place. Even adding an additional 100,000 residents to Florida's population, after removing GQI population, would still not result in an additional seat being apportioned to Florida.

⁹I obtained these totals from the Bureau's data portal: <https://api.census.gov/data/2020/dec/pl.html>.

VII. THE IMPACT OF DP AND GQI WITHIN FLORIDA IS UNCERTAIN

35. Because the purpose of applying DP methods to the decennial census is to protect the confidentiality of individual respondents, it is not possible to determine with confidence how the DAS affected population counts at small levels of geography, such as census blocks or voting tabulation districts (VTDs, which correspond closely to precincts). DP is a mathematical formalization of this statistical impossibility.

36. By design, errors introduced by the DAS are designed to cancel out on average. Indeed, they exactly cancel at the state level: the state's overall population is not affected by the DAS, as detailed above. Moreover, the DAS is designed to introduce much smaller errors at larger levels of geography (counties, congressional districts) than at smaller levels of geography (blocks, block groups). For example, the Bureau reports that the average error in population counts at the county level is 1.86 people.¹⁰

37. It is not possible to determine impact of GQI on any particular part of a state. There is no public record of which group quarters facilities were imputed, and disclosure of that information would definitionally violate the confidentiality of individual group quarters responses. Thus, it is not possible to determine with any precision which districts relatively gained or lost population due to GQI. Additionally, the total population imputed via GQI is just 0.077% of Florida's total population.

38. Overall, then, while the use of DP methods and GQI did change the reported population of some geographic units within Florida (though not the overall state population), these

¹⁰Table 1a of the "Detailed Summary Metrics" spreadsheet for the 2023-04-03 DAS production settings. Available at <https://www.census.gov/programs-surveys/decennial-census/decade/2020/planning-management/process/disclosure-avoidance/2020-das-development.html>.

changes are small in magnitude and cannot be localized to particular areas or districts based on publicly available information.

Pursuant to 28 U.S.C. § 1746, I declare under penalty of perjury that the foregoing is true and correct. Executed this 19th day of December, 2025.

A handwritten signature in blue ink, reading "Cory McCartan". The signature is written in a cursive style with a large initial "C" and a horizontal line extending from the end of the name.

Cory McCartan, Ph.D.

EXHIBIT A

Curriculum Vitae

Cory McCartan

Curriculum Vitae

September 2025

CONTACT INFORMATION	Department of Statistics, Penn State University 325 Thomas Building, 461 Pollock Road University Park, PA 16802	(425) 770-9244 mccartan@psu.edu
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ACADEMIC EMPLOYMENT	Pennsylvania State University Hoben and Patricia Thomas and Thomas and Ann Hettmansperger Early Career Professor of Statistics Assistant Professor of Statistics Affiliate Faculty in Political Science New York University Center for Data Science Data Science Assistant Professor / Faculty Fellow	2024 – 2024 – 2027 2024 – 2023 – 2024
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EDUCATION	Harvard University Ph.D., Statistics, 2023. Committee: Kosuke Imai (chair), Xiao-Li Meng, Gary King. Dissertation: <i>Computational and Bayesian Methods for Geographic Data in the Social Sciences</i> . A.M., Statistics, 2021. Grinnell College B.A., Mathematics, with honors, 2019.	2019 – 2023 2015 – 2019
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PEER-REVIEWED PUBLICATIONS	“Estimating Racial Disparities When Race is Not Observed,” with Robin Fisher, Jacob Goldin, Daniel E. Ho, and Kosuke Imai (2025). <i>Journal of the American Statistical Association</i> , Forthcoming. “Evaluating Bias and Noise Induced by the U.S. Census Bureau’s Privacy Protection Methods,” with Christopher T. Kenny, Tyler Simko, Shiro Kuriwaki, and Kosuke Imai (2024). <i>Science Advances</i> 10:18, eadl2524. “Measuring and Modeling Neighborhoods,” with Jacob R. Brown and Kosuke Imai (2024). <i>American Political Science Review</i> 118:4, 1966-1985. “Census Officials Must Constructively Engage with Independent Evaluations,” with Christopher T. Kenny, Tyler Simko, and Kosuke Imai (2024). <i>Proceedings of the National Academy of Sciences</i> 121:11, e2321196121. Letter to the editor re: Jarmin et al. (2023). “Making Differential Privacy Work for Census Data Users,” with Tyler Simko and Kosuke Imai (2023). <i>Harvard Data Science Review</i> 5:4.
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With response and rejoinder.

“Sequential Monte Carlo for Sampling Balanced and Compact Redistricting Plans,” with Kosuke Imai (2023). *Annals of Applied Statistics* 17:4, 3300-3323.

Covered by *The Washington Post*, *Quanta* magazine.

“Widespread Partisan Gerrymandering Mostly Cancels Nationally, but Reduces Electoral Competition,” with Christopher T. Kenny, Tyler Simko, Shiro Kuriwaki, and Kosuke Imai (2023). *Proceedings of the National Academy of Sciences* 120:25, e2217322120.

“Researchers Need Better Access to U.S. Census Data,” with Tyler Simko and Kosuke Imai (2023). *Science* 380:6648, 902-903.

“Recalibration of Predicted Probabilities Using the “Logit Shift”: Why Does it Work, and When Can it be Expected to Work Well?” with Evan T.R. Rosenman and Santiago Olivella (2023). *Political Analysis* 31:4, 651-661.

“Comment: the Essential Role of Policy Evaluation for the 2020 Census Disclosure Avoidance System,” with Christopher T. Kenny, Shiro Kuriwaki, Evan T.R. Rosenman, Tyler Simko, and Kosuke Imai (2023). *Harvard Data Science Review*, Special Issue 2.

Response to boyd and Sarathy (2022).

“Simulated Redistricting Plans for the Analysis and Evaluation of Redistricting in the United States,” with Christopher T. Kenny, Tyler Simko, George Garcia III, Kevin Wang, Melissa Wu, Shiro Kuriwaki, and Kosuke Imai (2022). *Nature: Scientific Data* 9:1, 689.

Covered by *The New York Times*.

“The Use of Differential Privacy for Census Data and Its Impact on Redistricting: the Case of the 2020 U.S. Census,” with Christopher T. Kenny, Shiro Kuriwaki, Evan T.R. Rosenman, Tyler Simko, and Kosuke Imai (2021). *Science Advances* 7:41, eabk3283.

Originally a Public Comment to the Census Bureau (May 28, 2021).

Covered by *The Washington Post*, the *Associated Press*, the *San Francisco Chronicle*, *NC Policy Watch*, and others.

“Geodesic Interpolation on Sierpinski Gaskets,” with Caitlin Davis, Laura LeGare, and Luke Rogers (2021). *Journal of Fractal Geometry* 8:2, 117-152.

WORKING PAPERS

“Identification and Semiparametric Estimation of Conditional Means From Aggregate Data,” with Shiro Kuriwaki (2025).

“Relative Bias Under Imperfect Identification in Observational Causal Inference,” with Melody Huang (2025). Under Review.

“The Role of Confounders and Linearity in Ecological Inference: A Reassessment,” with Shiro Kuriwaki (2025).

“Gerrymandering and Geographic Polarization Have Reduced Electoral Competition,” with Ethan Jasny, Christopher T. Kenny, Tyler Simko, Melissa Wu, Michael Y. Zhao, Aneetej Arora, Emma Ebowe, Philip O’Sullivan, Taran Samarth, and Kosuke Imai (2025). Under Review.

“Redistricting Reforms Reduce Gerrymandering by Constraining Partisan Actors,” with Christopher T. Kenny, Tyler Simko, Emma Ebowe, Michael Y. Zhao, and Kosuke Imai (2024). Under Review.

“Individual and Differential Harm in Redistricting,” with Christopher T. Kenny (2022). Under Review.

“Projective Averages for Summarizing Redistricting Ensembles” (2024).

“Finding Pareto Efficient Redistricting Plans with Short Bursts” (2024).

OTHER WRITING

“Candy Cane Shortages and the Importance of Variation.” International Statistical Institute: *Statisticians React to the News* (December 21, 2021).

“Where Will the Rocket Land?” International Statistical Institute: *Statisticians React to the News* (May 12, 2021).

“Who’s the Most Electable Democrat? It Might be Warren or Buttigieg, Not Biden.” *The Washington Post* (October 23, 2019).

“I-405 Express Toll Lanes: Usage, Benefits, and Equity,” with Shirley Leung, C.J. Robinson, Kiana Roshan Zamir, Vaughn Iverson, and Mark Hallenbeck. Technical report for the Washington State Department of Transportation (2019).

SOFTWARE

redist: Simulation Methods for Legislative Redistricting

seine: Semiparametric Ecological Inference

birdie: Bayesian Instrumental Regression for Disparity Estimation

bases: Basis Expansions for Regression Modeling

easycensus: Quickly Find, Extract, and Marginalize U.S. Census Tables

redistmetrics: Redistricting Metrics

adjustr: Stan Model Adjustments and Sensitivity Analyses using Importance Sampling

PL94171: Tabulate P.L. 94-171 Redistricting Data Summary Files

conformalbayes: Jackknife(+) Predictive Intervals for Bayesian Models

alarmdata: Download, Merge, and Process Redistricting Data

blockpop: Estimate Census Block Populations for 2020

ggredist: Scales, Geometries, and Extensions of ggplot2 for Election Mapping

tinytiger: Lightweight Interface to TIGER/Line Shapefiles

causaltbl: Tidy Causal Data Frames and Tools

wacolors: Colorblind-Friendly Palettes from Washington State

nbhdmodel: Neighborhood Modeling and Analysis

PRESENTATIONS

Invited

Oxford University, Dept. of Statistics. <i>Causal Inference Reading Group.</i>	May 2025
McMaster University, Faculty of Social Science. <i>Spark Talk Speaker Series.</i>	February 2025
University of North Carolina at Chapel Hill, Dept. of Political Science. <i>Methods and Design Workshop.</i>	February 2025
University of Wisconsin – Madison, Depts. of Political Science and Statistics. <i>Methods, Experiments, and Design Workshop.</i>	January 2025
Harvard Law School, Charles Hamilton Houston Institute for Race and Justice. <i>Guinier Project Research Roundtable.</i>	January 2025
Princeton University. <i>Frontiers in Data Science Symposium: Advances in Record Linkage.</i>	October 2024
Penn State University, Dept. of Political Science. <i>Colloquium Series.</i>	September 2024
New York University. <i>Math and Democracy Seminar.</i>	May 2024
Massachusetts Institute of Technology, Dept. of Political Science. <i>Political Methodology Speaker Series.</i>	September 2023
Harvard University, IQSS. <i>Applied Statistics Workshop.</i>	April 2023
Harvard University, IQSS. <i>Applied Statistics Workshop.</i>	October 2022
Harvard University, IQSS. <i>Applied Statistics Workshop.</i>	September 2021
Harvard University, IQSS. <i>Applied Statistics Workshop.</i>	September 2020

Conferences

Society for Political Methodology: 2025, 2024, 2023, 2022, 2022 (Poster), 2021 (Poster)
Small Area Estimation Conference: 2025 (Invited panel)
American Causal Inference Conference: 2025, 2024 (Poster)
Southern Political Science Association: 2025
Keystone State Statistics Symposium: 2024
Joint Statistical Meetings: 2024 (Invited paper panel), 2022 (Invited paper panel), 2021 (Invited paper panel)
ACM Conference in Equity and Access in Algorithms, Mechanisms, and Optimization: 2023
American Association for Public Opinion Research: 2022 (Poster)

TEACHING

Penn State University

STAT 440: Computational Statistics	Fall 2024, Fall 2025
STAT 597: Visualization and Communication in Statistics (special topic short course)	Fall 2025
STAT 597: Missing Data (special topic short course)	Fall 2024

New York University

DS-UA 111: Data Science for Everyone	Spring 2024
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Harvard University

STAT 117: Introduction to Biostatistics (Teaching Fellow)	Spring 2021
STAT 221: Monte Carlo Methods & Other Computational Tools for Statistical Learning (Teaching Fellow)	Fall 2020

Grinnell College

MAT 215: Linear Algebra (Peer Mentor)	Fall 2017, Spring 2019
MAT 310: Statistical Modeling (Peer Mentor)	Fall 2018
Grinnell College Math Lab	2018 – 2019

ADVISING **Ph.D. Committees**

Ross Cohen-Kristiansen (<i>co-chair</i> , Statistics, Penn State University)	2025 –
Tinghua Chen (Informatics, Penn State University)	2025 –
Kihyun Han (Statistics, Penn State University)	2025 –
Yang Yang (Political Science, Penn State University)	2025 –
Kyle McGovern (Bioinformatics and Genomics, Penn State University)	2025

M.S. Theses

Giovanni Stivella (Economics, University of Pisa and the Scuola Sant'Anna, Italy)	2025
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HONORS AND
AWARDS

Hoben and Patricia Thomas and Thomas and Ann Hettmansperger Early Career Professorship in Statistics, 2024 (total award: \$75,000).

Best Statistical Software Award, for developing statistical software that makes a significant research contribution; awarded to the redist software package by the Society for Political Methodology, 2022.

Certificate of Distinction in Teaching, awarded on the basis of student feedback by the Derek Bok Center for Teaching and Learning, 2021.

Pamela Ferguson Endowed Prize, awarded to up to two senior students by the Grinnell College Department of Mathematics, 2018.

SERVICE

Reviewer: *Proceedings of the National Academy of Sciences, Journal of the American Statistical Association, Annals of Applied Statistics, American Journal of Political Science, Quarterly Journal of Political Science, Harvard Data Science Review, Public Choice, Multiscale Modeling and Simulation, Discrete Applied Mathematics, Election Law Journal, Proceedings of the IASSL Triennial International Statistics Conference, Sloan Foundation.*

Discussant: 2024 PolMeth Conference, 2024 Midwest Political Science Association Annual Conference

Penn State University

Ph.D. admissions committee	2025 – 2026
Colloquium and SMAC Talk committee	2025 – 2026
Colloquium chair	2024 – 2025

New York University

Faculty fellow hiring review	2023 – 2024
MA admissions committee	2023 – 2024

Harvard University

Harvard Statistics Graduate Council	2020 – 2023
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Organized Ph.D. student retreat and research “lightning talks,” 2020 and 2021.

First-year Ph.D. Student Mentor 2020 – 2023

Harvard Graduate Students Union – UAW Local 5118 2019 – 2021

Elected member, Bargaining Committee, 2020–2021 and 2021–2024 contracts.

Interim chair, Finance and Benefits Committee, 2020.

OTHER EXPERIENCE	<p>CBS News 2024 –</p> <p>Election consulting and election night Data Desk</p> <p>Protect Democracy 2024</p> <p>Consultant, electoral reform modeling</p> <p>Data for Progress 2022</p> <p>Consultant, midterm election modeling</p> <p>University of Washington eScience Institute Summer 2019</p> <p>Data Science for Social Good Fellow</p> <p>Union of Grinnell Student Dining Workers 2016 – 2019</p> <p>Founder, President (2016–17), and Advisor to the Executive Board (2018–19)</p> <p>University of Connecticut Summer 2018</p> <p>REU Participant, Department of Mathematics</p> <p>Fred Hutchinson Cancer Research Center Summer 2017</p> <p>Lead Intern, Department of Biostatistics</p> <p>Cray, Inc. (now HPE) Summer 2015</p> <p>Intern, Chapel language testing</p>
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EXPERT REPORTS	<p><i>Cubanos Pa'lante v. Florida House of Representatives</i> (U.S. District Court for the Southern District of Florida, Case No. 1:24-cv-21983). Testified by deposition.</p> <p><i>Hodges v. Albritton</i> (U.S. District Court for the Middle District of Florida, Case No. 8:24-cv-879). Testified by deposition and at trial.</p> <p><i>McClure et al. v. Jefferson County Commission</i> (U.S. District Court for the Northern District of Alabama, Case No. 2:23-cv-00443). Testified by deposition and at trial.</p> <p><i>Callais et al. v. Landry</i> (U.S. District Court for the Western District of Louisiana, Case No. 3:24-cv-00122). Testified by deposition and at trial.</p> <p><i>GRACE, Inc. et al. v. City of Miami</i> (U.S. District Court for the Southern District of Florida, Case No. 1:22-cv-24066). Testified by deposition and at trial.</p> <p><i>Nairne et al. v. Ardoin</i> (U.S. District Court for the Middle District of Louisiana, Case No. 3:22-cv-0017). Testified by deposition and at trial.</p> <p><i>League of Women Voters v. Ohio Redistricting Commission</i> (Ohio Supreme Court, Case Nos. 2021–1193 and 2021–1449). Consultant (with Prof. Kosuke Imai).</p>
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