Mapping Methods in Contemporary Political Science Research:
An Analysis of Journal Publications (1998 - 2018)
Pre-Analysis Plan

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This document outlines the pre-analysis plan (PAP) for the project "Mapping Methods in Contemporary Political Science Research." The project surveys the conduct of political science research published in ten top journals from 1998 – 2018, based on original data collected from a sample of 1,926 research articles between July 2020 and May 2021.[1]

The document proceeds in five parts. First, we introduce the project's central research questions, the scope of our sample, and our codebook for original data collection. Second, we outline the descriptive information that we provide about the political science research articles in our sample, including the proportion of articles published in each year, each journal, and associated with each political science subfield or combinations of subfields. Third, we outline the descriptive statistics that we derive from supplementary information about authors in our sample, including the gender and racial / ethnic identities of the authors and the year that they completed their doctoral education. In this section, we also outline descriptive statistics about the modes of data collection and analysis in the articles in the sample. Fourth, we introduce hypotheses about relationships between methods of data collection and analysis and author gender, (doctoral) educational background, time, subfield, journal, and mode of data collection; we also discuss our methods for testing each hypothesis. Fifth, we introduce our analysis of supplementary information about the authors and editors of each journal in our sample. References follow.

Two appendices accompany this PAP: Appendix A discusses article selection and coding, and Appendix B is our codebook for article-level data collection..

The R code that accompanies this PAP, which we run on R 4.1.1, is located in **MMCPSR Analysis.R**.

Section 1: Research questions, sample, and codebook

This project documents the broad range of data-gathering techniques and analytic strategies that scholars use to generate knowledge about political phenomena by "mapping" the use of methods in contemporary political science research. Specifically, we analyze the data collection and generation techniques and methods of analysis employed in a specialized slice of political science scholarship – nearly 2,000 articles published in ten top disciplinary journals between 1998 and 2018 – to address a series of key questions. What data collection and generation

[1] We conducted exploratory analyses of data generated through coding 484 of the 1,926 articles in the sample for a draft version of the paper that we presented at the 2020 Annual Meeting of the American Political Science Association. We did not pre-register these analyses. This paper, including a Methodological Appendix that details the analysis, is available upon request.

techniques do contemporary political scientists employ – independently and in tandem? What methods of analysis do they use, and in what combinations? How do authors combine different ways of collecting, generating, and analyzing data in their work; how does their use differ across subfields and by author gender; and how has it changed over time?

Although our inquiry builds on previous surveys of how political scientists conduct research (Bennett, Barth, and Rutherford 2003; Levy 2007; Blanchard, Rihoux, and Álamos-Concha 2017), we depart from these previous studies by differentiating between methods of data *collection* and data *analysis* in contemporary research, and examining both. We also gather information about the gender, racial / ethnic identities, and (doctoral) educational backgrounds of authors in a subset of our sample of articles. These additional data contribute to an important literature on underrepresentation, diversity, and inclusion in the political science discipline (e.g., Teele and Thelen 2017; Shames and Wise 2017; American Political Science Association Task Force on Political Science in the 21st Century 2011).

To address our research questions, we collected data from a random sample of 1,926 articles published in ten top political science journals from 1998 – 2018 (Appendix A discusses our journal selection process). The 1,926 articles represent approximately one-quarter of all research articles published in these journals during this period. The journals are the *American Journal of Political Science (AJPS)*, *American Political Science Review (APSR)*, *British Journal of Political Science (BJPS), Journal of Politics (JOP)*, *Perspectives on Politics (PoP), International Organization (IO)*, *International Studies Quarterly (ISQ)*, *World Politics (WP)*, *Comparative Politics (CP)*, and *Comparative Political Studies (CPS)*.

Once we had selected the articles to analyze, we developed and refined our codes for data collection through an iterative process. During the spring and summer of 2019, we drafted an initial codebook that sought to address three core research questions: (1) what is the structure of authorship in articles published in highly ranked journals, and to what subfield do the articles correspond; (2) what techniques are employed to collect and/or generate the empirical base of those articles; and (3) what methods are employed to analyze the data that underpin that work? We solicited feedback on our initial codebook from various faculty at our home institution and beyond. We also refined the codebook through 14 week-long rounds of practice coding in Dedoose, a qualitative data analysis software, using out-of-sample articles drawn from the same ten journals.

The final version of the codebook (see Appendix B) includes codes focusing on the same three aspects of each article on which the initial codebook focused. First, the codebook addresses the structure of authorship (and gender of authors) and the subfield(s) to which the analysis in each article corresponds. Second, the codebook addresses data collection and generation techniques, with codes differentiating between techniques that do and do not involve interactions between researchers and human participants or interlocutors in both observational and experimental settings. And lastly, the codebook addresses forms of data analysis. We also derived a set of "sui generis" codes to describe additional attributes of the articles in the sample (e.g., whether it drew on a natural experiment).

Once we finalized the codebook, we used Dedoose to code the articles in our sample (N=1,926). This coding took place between July 2020 and July 2021.

To create our final dataset, we exported the Media and Code Presence files from Dedoose into Excel. The Media file includes the title of each article uploaded, year and journal descriptors, as well as a variable for each code indicating the frequency with which it was applied to all articles. The Code Presence file includes the title of each article and a binary variable for each code indicating application regardless of frequency. Both files included entries for the full sample of 1,926 articles. We merged the two files in R. The resultant file included the article title, the year of publication, the journal title, and binary indicators for each code. The unit of observation for the main dataset is the article.

In Appendix A, we provide a detailed description of the development of the codebook, coding, our intercoder reliability measures, and our checks to ensure that we had fully coded all articles in the sample. In Appendix B, we provide our detailed codebook.

All measures described below are based on these data, except measures of (1) the self-described gender and racial / ethnic identities of authors; (2) the years and disciplines in which the authors received their doctoral degree; and (3) the gender and subfield of the editors of the 10 journals in our sample from 1998 to 2018. With the help of an undergraduate research assistant, we created a separate "Author and Editor Database" including all of the authors of all of the articles in the sample (N=2,743), and all of the scholars who had served as lead or high-ranking editors of the ten journals under study during the time period of interest. We collected information about subfields and institutional affiliations based on Google searches and mainly drawing information from their personal or institutional websites. Using this information to identify the individuals in this database, the American Political Science Association (APSA, the largest professional association of political scientists in the United States) provided information about these individuals' self-described gender and racial / ethnic identities drawn from APSA's member and publication databases.

We collected data about authors' PhD graduation year and training through a separate process that relied on information from authors' personal or institutional websites, which we discuss in Section 1B below..

A. *Finalizing the demographic data from APSA*

The APSA data include the self-described *gender* and *race / ethnicity* for each author. The gender variable includes categories for male, female, and non-binary, as well as a category for authors who decline to disclose their gender identity. The race / ethnicity variable includes a series of default racial / ethnic categories, which we describe in Section 3B below, as well as (1) an "Other" category and (2) a category for authors who decline to disclose their racial / ethnic identity. We used the following procedure to sort through the matches in the combined_file folder. The R file associated with this procedure is titled **apsa_race_ethnicity.R**:

1. We loaded the four separate datasets that APSA researchers generated from their database: (1) FirstName_MI_LastName.matches.csv, (2) FirstName_LastName.matches.csv, (3) FirstInitial_LastName.matches.csv, and (4) nomatches2.csv.

2. Then, we identified duplicate entries using the "kap_index" variable. The number of duplicate entries totaled 508.

3. Then, we created a new "delete" variable to identify duplicate entries to remove from the dataset. For this variable, a value of 1 indicates that the entry is a duplicate that we later remove from the dataset; a value of 0 indicates that I keep the entry in the dataset. Coding this variable involved a combination of computer-generated and manual procedures, as follows.

   Computer-generated: After creating the variable, we calculated the string distance between the name of the author's institutional affiliation in our database and in APSA's database. We automatically set the delete variable to 0---indicating a match---for observations with an "institutional affiliation" string distance of 2 or less. We then set the value of the delete variable to 1 for the other duplicate observations in the kap_index group. We also deduplicated observations to remove duplicates that may have resulted from NA values in either the APSA dataset or our dataset.

   Manual: Then, we downloaded the dataset to evaluate the remaining "uncertain" entries by hand. The remaining entries totaled 181 observations. We manually identified matches (delete = 0, all other observations associated with the kap_index group = 1) using one of the following criteria:

   a. The institutional affiliation in the APSA database and the institutional affiliation in our database are identical, but each database refers to them by a different name. For example, University of London, Birkbeck College is also known as Birkbeck University of London. The string distance between the institution names is 27, however, so we were only able to identify this match via visual comparison;

   b. The APSA database and our database identify institutions with which the author has been affiliated at different stages of their career, according to their personal website, faculty website, or CV;

   c. There was a typo in the institutional affiliation in our database; after correcting the typo, the institutional affiliation listed in the APSA database matched the institutional affiliation listed in our database;

   d. The author was affiliated with multiple institutions listed in the APSA database. In these circumstances, we marked the delete variable as 0 for the observation that includes author's most recent institutional affiliation, according to their personal website, faculty website, or CV, and marked the delete variable as 1 for all other observations;

e. None of the listed institutions in the APSA database match the institution listed in our database or an institution with which the author was previously affiliated, but there is a "NA" institutional-affiliation entry in the APSA database. In these circumstances, we marked the delete variable as 0 for the observation that lists the institutional affiliation in the APSA database as "NA," and marked the delete variable as 1 for all other observations.

4. The combination of computer-generated and manual coding identified 317 (out of 2,707) duplicate observations that we removed from the dataset. The remaining observations totaled 2,390, compared to 2,403 in the original author database.

These revisions resulted in the following four CSV-formatted datasets, which we may provide on request:

- final_apsa_list: The final list of authors with information from (1) the APSA membership database and (2) our original PhD data.

- author_level_final: The author-article-level version of final_apsa_list, with dummy variables for gender and race / ethnicity.

- gender_article: An author-article-level dataset of gender / author structure information. The "article_title" variable corresponds to the article codes that we use in the main project dataset.

- race_ethnicity_article: An author-article-level dataset of race and ethnicity / author structure information. The "article_title" variable corresponds to the article codes that we use in the main project dataset.

B. Collecting information about PhD graduation years

In response to feedback that we received during a paper presentation at the 2021 APSA Annual Meeting, we also collected information about the PhD graduation years and disciplinary training of the authors in the sample. In Section 4 below, we describe our analytic procedure for testing hypotheses about the relationship between PhD graduation year and training---our measure of initial exposure to new analytic methods in the discipline---and methods of data collection and analysis.

We focused exclusively on PhD training in political science because we are interested in the relationship between methodological training in the discipline and methodological practices. For this reason, we did not collect information on PhD training in disciplines beyond political science and other cognates (e.g., politics, government).

Our analysis employs two main author-level variables. The first, *PhD year*, includes the following values:

1. **PhD Year**: An integer value recording the year in which the author received their PhD in a relevant program;
2. **Not PS PhD**[2]: the author holds a PhD in a discipline other than PS, etc.
3. **PNDG**: The author is currently enrolled in a relevant PhD program;
4. **No PhD**: The author does not hold a PhD;
5. **NAV**: The year the author received a PhD in a relevant discipline is either unavailable or it is unclear whether the author holds a PhD.

The second, *PhD institution*, includes the following values:

1. **PhD institution name**: The name of the institution that granted the author their relevant PhD or at which they are currently pursuing a relevant PhD. The PhD institution variable only carries this value if PhD year carries an integer value or PNDG.
2. **Not PS PhD**: the author holds a PhD in a discipline other than PS, etc. We include the following "edge" categories in the Not PS PhD category, and exclude these programs from the category of "Political Science PhD programs":
    a. Public Administration
    b. Public Policy
    c. Political Communication
    d. Policy Analysis
    e. Social Science
    f. International Development
3. **No PhD**: The author does not hold a PhD.
4. **NAV**: The institution that granted the author their relevant PhD is unavailable or it is unclear whether the scholar has completed a relevant PhD.

Section 2: Articles in the sample

We present the following descriptive information about the articles in the sample:

- *Number of articles published per year*: The count of all articles published in all journals included in the project in each year from 1998 to 2018.

- *Number of articles published in each journal*: The count of all articles published in each journal in all years from 1998 to 2018.

[2] During the Spring 2022 semester, we added an additional category for the PhD Year and PhD Institution codes, "Not PS PhD," to differentiate between authors without any PhD and those authors without a PhD in Political Science or cognate disciplines. We applied this code to all authors (1) whom we had identified as an affiliate of a department other than Political Science, Government, Politics, or a cognate discipline or subfield and (2) for whom we had previously entered a "No PhD" value in either the "PhD Year" and "PhD Institution" categories.

- *Number of articles published per year in each journal*: The count of all articles published in each journal, in each year from 1998 to 2018.

- *Subfield*: We calculate the count and proportion of articles associated with (1) Comparative Politics (CP) exclusively; (2) American Politics (AP) exclusively; (3) International Relations (IR) exclusively; (4) Political Theory (PT) exclusively; (5) Methodology exclusively; (6) Conceptualization and Measurement exclusively; (6) CP and IR; (7) AP and IR; and (8) Methodology and all other subfield categories. To calculate the proportion of articles, we divide the count of all articles in each category by the total number of articles in the sample.

  We also calculate the count and proportion of articles written by authors associated with each subfield in the APSA dataset. Because "self-identified subfield" and "article subfield" are different categories of subfield information, readers should not interpret this second calculation as a direct robustness check on the first.

- *Number of articles in each subfield published in each journal*: The count of all articles published in each of the six subfields, in each journal.

Section 3: Descriptive statistics about author and article parameters

We present the following descriptive statistics about the gender, racial / ethnic identities, and subfields of the authors of each article, as well as about the articles' mode of inquiry, the overall empirical basis of the analysis, the type of observational / experimental human-participant research on which it was based (if any), the data sources drawn on for observational or experimental human-participant research (if any), and the type of analysis used, as well as about three sui generis data/analysis attributes.

A. Article-level attributes: Full sample

- *Gender and authorship structure*: We calculate the count and proportion of articles that are (1) single-authored by a woman; (2) single-authored by a man; (3) co-authored by an all-women team; (4) co-authored by an all-men team; (5) co-authored by a team of women and men; (6) authored by any women, including single-authored, all-women, and mixed-gender teams; (7) authored by any men, including single-authored, all-men, and mixed-gender teams. To calculate the proportion of articles, we divide the count of all articles in each category by the total number of articles in the sample.

With regard to *Racial / ethnic identity categories*: Because the APSA demographics form does not constrain the racial / ethnic categories with which members self-identify nor the number of categories with which they identify, members self-sort into various racial / ethnic categories that may not conform to common census categories. We use the following default categories from the APSA demographics form: (1) Non-Hispanic White or Euro-American; (2) Black, African American, or Afro-American; (3) East Asian or Asian American; (4) South Asian or Indian American; (5) Latino or Hispanic American; (6) Middle Eastern or Arab American; (7) Native

American or Alaskan Native; (8) Native Hawaiian or Other Pacific Islander. We create binary variables for each of these categories, with a value of 1 indicating that the author identifies with the racial / ethnic category, and a value of 0 indicating that they do not.

In the White category, we also include any category in which the author describes themselves as "White," regardless of national or regional origin. We do not interpret references to European nationalities as evidence that the author self-identifies as White. If the author identifies as "mixed" and specifies the categories that comprise their multiracial identity, or else lists multiple racial / ethnic categories with which they identify, we assign a value of 1 to each category with which the author identifies. If the author identifies as "mixed" and does not specify these categories, we do not assign a value of 1 to any specific category.

We create an Other category for all self-identified racial / ethnic categories that do not align with the above criteria. For the purposes of this analysis, we treat "Prefer not to disclose" answers to the APSA demographics form as missing values.

- *Racial / ethnic identity and authorship structure*: We calculate the count and proportion of articles authored *only* by people who self-identify with the racial / ethnic categories described above. These categories are not mutually exclusive because authors may either self-identify as multi-racial, or may self-identify as Hispanic or Latino (an ethnic category, according to the US census) and as members of other racial groups.

  We also calculate the count and proportion of articles authored by a combination of White and non-White people, to assess the extent of multi-racial / ethnic collaborations.

  To calculate the proportion of articles, we divide the count of articles in each category by the total number of articles in the sample for which we have information about the racial / ethnic identities of all authors. We omit all NA values from this calculation..

- *Gender by subfield, time, and journal*: We calculate the count and proportion of articles associated with the gender and authorship structure categories as they vary by (a) subfield; (b) time (year); and (c) journal. To calculate the proportion of articles, we divide the count of articles in each "crosstab" (e.g., the combination of gender and authorship structure and subfield) category by the total number of articles in the subfield, time, or journal categories for which we have information about the racial / ethnic identities of all authors.

B. Author-level attributes: Full sample

- *Gender self-identification*: Because we used author names to infer the author gender identities and authorship structure of each *article*, we also use data from the APSA member database as a measurement check on the gender identities of *authors* in the sample. First, we present the count and proportion of gender identities in the sample, differentiating between authors who self-identify (1) as men, (2) as women, and (3) as non-binary. Second, to facilitate this measurement check, we recreate the authorship structure measure from our original database. Based on the APSA database, we identify articles that have (1) only male authors; (2) only female authors; (3) only-male multi-author teams; (4) only-female multi-author teams; and (5) mixed-gender multi-author teams, including non-binary authors. We estimate the Pearson's *r* on the relationship between the authorship structure measures based on our original inferences from author names, and the APSA self-identification data.

- *Racial / ethnic identity*: Based on the APSA database, we present the count and proportion of authors who self-identify with the racial / ethnic categories that we describe above. To calculate the proportion of authors, we divide the count of authors in each category by the total number of authors in the sample for which we have information about the racial / ethnic identities of all authors. We omit all NA values from this calculation.

- *Number of authors in and outside the discipline:* The count of all authors in the sample with a PhD by discipline (political science and non-political science).

- *Average number of articles per author:* The average number of articles published per author with a completed or pending political science PhD.

- *Number of authors by number of articles published:* The count of all authors with a completed or pending political science PhD. by the number of articles they published.

- *Average years from PhD to publication:* The average number of years between an author's completion of a political science PhD and the publication of an article.[3]

- *Average years from PhD. to publication by publication year:* The average number of years between an author's completion of a political science PhD and the publication of an article for each publication year from 1998 to 2018.

- *Number of authors by PhD year*: The number of authors with a political science PhD by the year of PhD completion.[4]

- *Number of authors by seniority*, *by year:* The number of authors with a completed or pending political science PhD by seniority by year.

C. Article-level attributes: Restricted sample

For the following attributes, we use a restricted sample of articles that excludes all articles that we coded as both (1) associated with the PT subfield and (2) having "No discernible method." As we describe in Appendix A, these articles lack an empirical basis and a mode of analytic inquiry that corresponds to dominant methods in AP, CP, and IR. We exclude the PT / No discernible method articles from the restricted sample to avoid inflating the denominator (total

[3] Graduate students are coded as 0.
[4] Graduate students are not assigned a year of completion and are instead coded as pending.

articles in the sample) when calculating proportions of articles associated with different forms of data collection and analysis.

- *Mode of inquiry*: We calculate the count and proportion of articles that drew on data the author generated (as opposed to exclusively using information collected from pre-existing sources) using (1) observational techniques; (2) experimental techniques; or (3) both observational and experimental techniques. Category (1) includes observational techniques involving both human participant and non-human participant-based forms of data collection. To calculate the proportion of articles, we divide the count of articles in each category by the total number of articles in the restricted sample.

- *Empirical basis of analysis*: We calculate the count and proportion of articles that use data (1) only from pre-existing sources; (2) only from author-generated sources, but excluding human participants; (3) only from author-generated sources, involving human participants with an observational sampling strategy; or (4) only from author-generated sources, involving human participants with an experimental sampling strategy. To calculate the proportion of articles, we divide the count of articles in each category by the total number of articles in the restricted sample.

  We also calculate the count and proportion of articles that use data from both pre-existing and author-generated sources. For these articles, we calculate the count and proportion that (1) tended towards relying on pre-existing sources or (2) tended towards relying on author-generated data. To calculate the proportion of articles, we divide the count of articles in each category by the total number of articles in the sample of articles that use data from both pre-existing and author-generated sources.

- *Type of observational human-participant research*: We calculate the count and proportion of articles that use data from (1) ethnography or participant observation, exclusively; (2) ethnography or participant observation, in combination with any other data-collection technique; (3) interviews and focus groups, exclusively; (4) interviews and focus groups, in combination with any other data-collection technique; (5) survey methods, exclusively; or (6) survey methods, in combination with any other data-collection technique. To calculate the proportion of articles, we divide the count of articles in each category by the total number of articles in the restricted sample.

  We also calculate the count and proportion of articles associated with each category of observational human-participant research as they vary by (a) subfield; (b) time (year); and (c) journal. To calculate the proportion of articles, we divide the count of articles in each crosstab category by the total number of articles in the subfield, time, or journal categories.

- *Type of experimental human-participant research*: We calculate the count and proportion of articles that use data from (1) survey experiments, exclusively; (2) survey experiments, in combination with any other data-collection technique; (3) field experiments, exclusively; (4) field experiments, in combination with any other data-collection technique; (5) lab experiments, exclusively; or (6) lab experiments, in combination with any other data-collection technique. To calculate the proportion of articles, we divide the count of articles in each category by the total number of articles in the restricted sample.

We also calculate the count and proportion of articles associated with each category of experimental human-participant research as they vary by (a) subfield; (b) time (year); and (c) journal. To calculate the proportion of articles, we divide the count of articles in each crosstab category by the total number of articles in the subfield, time, or journal categories.

- *Source of observational or experimental human-participant research*: We calculate the count and proportion of articles involving either observational or experimental human-participant research that drew on interaction with individuals (1) employed by international organizations or institutions; (2) employed by domestic governments; (3) employed by civil society organizations; (4) employed by media organizations; or (5) employed as academics or researchers. To calculate the proportion of articles, we divide the count of articles in each category by the total number of articles in the restricted sample.

  We also calculate the count and proportion of articles associated with each category of interlocutors as they vary by (a) subfield; (b) time (year); and (c) journal. To calculate the proportion of articles, we divide the count of articles in each crosstab category by the total number of articles in the subfield, time, or journal categories.

- *Type of single-method analysis*: We calculate the count and proportion of articles that use only (1) interpretive methods; (2) qualitative methods, including (a) process tracing, (b) qualitative comparative analysis (QCA), (c) congruence analysis, (d) counterfactual analysis, (e) structured case comparison, or (f) another unspecified form of qualitative analysis; (3) illustrative case studies; (4) quantitative methods, including (a) simple probability, (b) regression, (c) statistics with an identification strategy, and (d) machine learning; (5) formal modeling; and (6) no discernible method. To calculate the proportion of articles, we divide the count of articles in each category by the total number of articles in the restricted sample.

- *Type of multi-method analysis*: We calculate the count and proportion of articles that use (1) more than one method; (2) more than one qualitative method, excluding quantitative and interpretive methods, and formal modeling; (3) one or more qualitative methods and a quantitative method; (4) one or more qualitative methods and formal modeling; and (5) a quantitative method and formal modeling. To calculate the proportion of articles, we divide the count of articles in each category by the total number of articles in the restricted sample.

  For Categories (1), we calculate the count and proportion of articles that tended to (1) rely overwhelmingly on qualitative analysis; (2) rely overwhelmingly on formal modeling; (3) rely overwhelmingly on quantitative analysis; (4) rely overwhelmingly on interpretive methods; and (5) had no specific methodological focus. To calculate the proportion of articles, we divide the count of articles that tend towards each category of multi-method work by the total number of multi-method articles.

For Categories (3) and (4), we also calculate the count and proportion of articles that tended to rely overwhelmingly on qualitative analysis. To calculate the proportion of articles, we divide the count of articles that tend towards each category of multi-method work by the total number of multi-method articles.

- *Natural experiments*: We calculate the count and proportion of articles that claim to analyze data derived from a "natural experiment". To calculate the proportion of articles, we divide the count of articles in the category by the total number of articles in the restricted sample.

  We also calculate the count and proportion of articles referencing a "natural experiment" as they vary by year. To calculate the proportion of articles, we divide the count of "natural experiment" articles published in each year by the total number of articles in the restricted sample published in the same year.

- *Synthetic data*: We calculate the count and proportion of articles that use synthetic data as the empirical basis of the analysis. To calculate the proportion of articles, we divide the count of articles in the category by the total number of articles in the restricted sample.

  We also calculate the count and proportion of "synthetic data" articles as they vary by year. To calculate the proportion of articles, we divide the count of "synthetic data" articles published in each year by the total number of articles in the restricted sample published in the same year.

- *Text mining and analysis*: We calculate the count and proportion of articles that use text mining or text analysis. To calculate the proportion of articles, we divide the count of articles in the category by the total number of articles in the restricted sample.

  We also calculate the count and proportion of "text mining / analysis" articles as they vary by year. To calculate the proportion of articles, we divide the count of "text mining / analysis" articles published in each year by the total number of articles in the restricted sample published in the same year.

Section 4: Analysis of relationships among article parameters

We also estimate a series of bivariate correlations and probit regressions to describe the relationships between multiple variables in the sample. For each set of dependent and independent variables discussed in this section we outline (1) hypotheses about their anticipated relationship; (2) how we operationalize the variables; (3) the statistical strategy that we use to test these hypotheses; and (4) the sample on which we conduct these analyses.

Estimation strategy: For all analyses, we calculate Pearson's *r* where we have no strong expectations about the direction of the "causal arrow" between two variables. Otherwise, we estimate both bivariate ordinary least squares (OLS) and probit regression models to characterize the relationship between more clearly defined independent and dependent variables. Because each outcome variable in our analysis is binary, the OLS and probit model specifications correspond to the potential linear or non-linear shape of the relationship, respectively. We present marginal effects for all probit models. In the title for each set of hypotheses, we use "<>" to indicate an unclear directional relationship, and ">" to indicate a clearer directional relationship.

Consistent with convention, we use $\alpha = 0.05$ as our threshold for statistical significance for all models. We report p-values and unstandardized coefficients for all models.

Sample: As in Section 3C above, we restrict the analyses that we discuss below to exclude articles that we coded as associated with the PT subfield and having "No discernible method." In describing the analyses below, we use "Default" to indicate this subset sample. We subset subsequent samples on the basis of this default sample.

1. Time > Experimental data collection

- H1: The use of data generated through experiments has increased over time (Druckman et al. 2006).
- Dependent variable: Use of experimental data, where 1 indicates that the article employs experimental data, and 0 indicates that it does not.
- Independent variable: Year
- Estimation strategy: OLS, probit
- Expected coefficient value: Positive
- Sample: Default

2. Subfield > Experimental data collection

- H2: Articles in the CP subfield are more likely to rely on data generated through experiments than articles in the AP subfield (Lupu and Michelitch 2018).
- Dependent variable: Use of experimental data, where 1 indicates that the article employs experimental data, and 0 indicates that it does not.
- Independent variable: Subfield, with separate correlation estimates for AP, CP, IR, PT, Conceptualization and Measurement, and Methodology.
- Estimation strategy: OLS, probit
- Expected coefficient value: For CP, positive; for AP, null.
- Sample: Default

3. Time > Author-generated data

- H3a: The use of exclusively or mostly author-generated data has increased over time (Kapiszewski et al. 2015).
- H3b: The use of exclusively or mostly author-generated data has decreased over time.
- Dependent variable: Use of (1) exclusively author-generated data or (2) a combination of author-generated and pre-existing data that tends towards author-generated data. For this

variable, 1 indicates that the article employs exclusively or mostly author-generated data, and 0 indicates that it does not.

- Independent variable: Year
- Estimation strategy: OLS, probit
- Expected coefficient value: (H3a) Positive; (H3b) Negative
- Sample: Default

*4. Time * Top cross-subfield journals > Author-generated data*

- H4: The increase in the use of exclusively or mostly author-generated data over time is especially pronounced in top cross-subfield journals.
- Dependent variable: Use of exclusively or mostly author-generated data. See models associated with H3a and H3b.
- Independent variable: Year
- Interaction term: Publication in top cross-subfield journals, as defined by articles published in APSR, AJPS, or JOP. We select these three journals because both Giles and Garand (2007) and Garand et al. (2009)---the two journal rankings that we used to select our sample of articles---present these as the "highest-ranking" all-subfield journals, as measured by both impact factor and perceived ranking by political scientists. Based on impact factors in 2021, these journals continue to rank higher than BJPS and PoP, the two other all-subfield journals in the sample. For this variable, 1 indicates that the article was published in one of these three journals, and 0 indicates that it was not.
- Estimation strategy: OLS, probit
- Expected coefficient value for interaction term: Positive
- Sample: Default

5. Subfield > Author-generated data

- H5: Articles in the CP subfield are more likely to rely exclusively or mostly on author-generated data than articles in the IR or AP subfields (Kapiszewski et al. 2015).
- Dependent variable: Use of exclusively or mostly author-generated data. See models associated with H3a and H3b.
- Independent variable: Subfield, with multinomial estimates for AP, CP, IR, PT, Conceptualization and Measurement, and Methodology.
- Estimation strategy: OLS, probit
- Expected coefficient value: For CP, positive; for IR and AP, null.
- Sample: Default

6a. Gender > Interpretive methods, exclusively

- H6a: Women are more likely to author articles using interpretive methods, exclusively (Evans and Moulder 2011; Teele and Thelen 2017; Shames and Wise 2017).
- Dependent variable: Use of interpretive methods, where 1 indicates that the article uses interpretive methods, exclusively, and 0 indicates that it does not.
- Independent variable, version 1: Gender of the author team, with multinomial estimates for "Single-authored male," "Single-authored female," "Co-authored male," "Co-authored female," and "Co-authored mixed gender team."
- Estimation strategy: OLS, probit

- Expected coefficient value: For Single-authored female, Co-authored female, and Co-authored mixed gender team, positive.
- Sample: Default

6b. Gender > Interpretive methods, exclusively

- H6b: Women are more likely to author articles using interpretive methods, exclusively.
- Dependent variable: Use of interpretive methods, where 1 indicates that the article uses interpretive methods, exclusively, and 0 indicates that it does not.
- Independent variable, version 2: Gender of the author team, where 1 indicates that the article is authored by "Single-authored female" or "Co-authored female" teams, and 0 indicates that the article is authored by "Single-authored male," "Co-authored male," or "Co-authored mixed gender" teams.
- Estimation strategy: OLS, probit
- Expected coefficient value: For Single-authored female and Co-authored female, positive.
- Sample: Default

6c. Gender > Interpretive methods, exclusively or in tandem with other methods

- H6c: Women are more likely to author articles using interpretive methods.
- Dependent variable: Use of interpretive methods, where 1 indicates that the article uses interpretive methods, and 0 indicates that it does not.
- Independent variable, version 1: Gender of the author team, with multinomial estimates for "Single-authored male," "Single-authored female," "Co-authored male," "Co-authored female," and "Co-authored mixed gender team."
- Estimation strategy: OLS, probit
- Expected coefficient value: For Single-authored female and Co-authored female, positive.
- Sample: Default

6d. Gender > Interpretive methods, exclusively or in tandem with other methods

- H6d: Women are more likely to author articles using interpretive methods.
- Dependent variable: Use of interpretive methods, where 1 indicates that the article uses interpretive methods, and 0 indicates that it does not.
- Independent variable, version 2: Gender of the author team, where 1 indicates that the article is authored by "Single-authored female" or "Co-authored female" teams, and 0 indicates that the article is authored by "Single-authored male," "Co-authored male," or "Co-authored mixed gender" teams.
- Estimation strategy: OLS, probit
- Expected coefficient value: For Single-authored female, Co-authored female, and Co-authored mixed gender team, positive.
- Sample: Default

7. Gender > Qualitative methods, exclusively

- H7: Women are more likely to author articles using qualitative methods, exclusively (Evans and Moulder 2011; Teele and Thelen 2017; Shames and Wise 2017).
- Dependent variable: Use of only qualitative methods, where 1 indicates that the article uses only qualitative methods, and 0 indicates that it does not.

- Independent variable: Gender of the author team. See model associated with H6a.
- Estimation strategy: OLS, probit
- Expected coefficient value: For Single-authored female, Co-authored female, and Co-authored mixed gender team, positive.
- Sample: Default

8. Gender > Qualitative methods, exclusively or in tandem with other methods

- H8: Women are more likely to author articles using qualitative methods, exclusively or in tandem with other methods.
- Dependent variable: Use of qualitative methods, where 1 indicates that the article uses qualitative methods, exclusively or in tandem with other methods, and 0 indicates that it does not.
- Independent variable: Gender of the author team. See model associated with H6a.
- Estimation strategy: OLS, probit
- Expected coefficient value: For Single-authored female, Co-authored female, and Co-authored mixed gender team, positive.
- Sample: Default

9. Time > Quantitative methods, exclusively or in tandem with other methods

- H9: The use of quantitative methods, exclusively or in tandem with other methods, has increased over time (Bennett et al. 2003; Emmons and Moravcsik 2020).
- Dependent variable: Use of quantitative methods, where 1 indicates that the article uses quantitative methods, exclusively or in tandem with other methods, and 0 indicates that it does not.
- Independent variable: Year
- Estimation strategy: OLS, probit
- Expected coefficient value: Positive
- Sample: Default

10. Time > Quantitative methods, exclusively

- H10: The use of quantitative methods independently (not in tandem with another method) has increased over time.
- Dependent variable: Use of quantitative methods, where 1 indicates that the article uses only quantitative methods, and 0 indicates that it does not.
- Independent variable: Year
- Estimation strategy: OLS, probit
- Expected coefficient value: Positive
- Sample: Default

11. Time > Causal identification strategy

- H11: The use of causal identification strategies has increased over time (Imai 2011; Clark and Golder 2015).
- Dependent variable: Use of causal identification strategies. We test this hypothesis using three separate measures, as follows; for each, 1 indicates that the article uses the listed methods of data collection or analysis, and 0 indicates that it does not:

- Model 11a: The use of statistics with an identification strategy or experimental data collection methods;
- Model 11b: The use of statistics with an identification strategy, regression involving fixed effects, or experimental data collection methods; and
- Model 11c: The use of statistics with an identification strategy, regression involving fixed effects, qualitative process tracing methods, or experimental data collection methods

- Independent variable: Year, squared. This variable estimates the differential effect of later years on the likelihood of causal identification strategies, as we posit that the increase in the use of causal identification strategies accelerates over time
- Estimation strategy: OLS, probit. We estimate separate models for each dependent variable.
- Expected coefficient value: Positive
- Sample: Default

12. Time > Formal modeling, exclusively

- H12: The use of formal modeling independently (i.e., not in tandem with another method) has decreased over time (Little and Pepinsky 2016).
- Dependent variable: Use of formal modeling, where 1 indicates that the article uses only formal modeling methods, and 0 indicates that it does not.
- Independent variable: Year
- Estimation strategy: OLS, probit
- Expected coefficient value: Negative
- Sample: Default

13. Time > Formal modeling, exclusively or in tandem with other methods

- H13: The use of formal modeling, exclusively or in tandem with other methods, has decreased over time.
- Dependent variable: Use of formal modeling, exclusively or in tandem with other methods, where 1 indicates that the article uses formal modeling, and 0 indicates that it does not.
- Independent variable: Year
- Estimation strategy: OLS, probit
- Expected coefficient value: Negative
- Sample: Default

14. Time > Explicit qualitative methods

- H14: The use of explicit qualitative methods, exclusively or in tandem with other methods, has increased over time (George and Bennett 2005; Collier and Brady 2004; Morgan 2016).
- Dependent variable: Use of "explicit" qualitative methods, exclusively or in tandem with other methods, where 1 indicates that the article uses (1) process tracing; (2) structured case comparison; (3) QCA; (4) congruence analysis; and / or (5) counterfactual analysis, and 0 indicates that it does not.
- Independent variable: Year

- Estimation strategy: OLS, probit
- Expected coefficient value: Positive
- Sample: The subset of all articles that use qualitative methods.

15. Time > Implicit qualitative methods

- H15: The use of implicit qualitative methods, exclusively or in tandem with other methods, has decreased over time.
- Dependent variable: Use of "implicit" qualitative methods, exclusively or in tandem with other methods, where 1 indicates that the article uses (1) an unspecified form of qualitative analysis (noted in the codebook as "Qualitative - Other," or (2) an illustrative case study, and 0 indicates that it does not.
- Independent variable: Year
- Estimation strategy: OLS, probit
- Expected coefficient value: Negative
- Sample: The subset of all articles that use qualitative methods.

16. Years since 2004 > Process tracing

- H16: The use of process tracing, exclusively or in tandem with other methods, has increased since 2004.
- Dependent variable: Use of process tracing methods, exclusively or in tandem with other methods, where 1 indicates that the article uses process tracing, and 0 indicates that it does not.
- Independent variable, version 1: Year, as an interval value.
- Independent variable, version 2: Year, as a multinomial estimate.
- Estimation strategy: OLS, probit
- Expected coefficient value: Positive
- Sample: Default

17. Years prior to, and since 2012 > Multi-method research (combining quantitative and qualitative methods)

- H17: The use of multi-method research (combining quantitative and qualitative methods) increased prior to 2012, and decreased after 2012 (Gerring 2011; Goertz and Mahoney 2012).
- Dependent variable: Use of both quantitative and qualitative methods, where 1 indicates that the articles uses a combination of quantitative and qualitative methods, and 0 indicates that it does not.
- Independent variable, version 1: Year, as an interval value.
- Independent variable, version 2: Year, as a multinomial estimate.
- Estimation strategy: OLS, probit
- Expected coefficient value: Positive before 2012, negative in 2012 and subsequent years
- Sample: Default

18. Time > Use of quantitative methods, exclusively or in tandem with other methods, among women authors

- H18: The use of quantitative methods by women authors has not changed over time.

- Dependent variable: Use of quantitative methods, exclusively or in tandem with other methods. See models associated with H9.
- Independent variable, version 1: Year, as an interval value.
- Independent variable, version 2: Year, as a multinomial estimate.
- Interaction term: Gender of the author team, where 1 indicates that the article was “Single-authored by a female” or “Co-authored by an all-female team,” and 0 indicates that the article was not.
- Estimation strategy: OLS, probit
- Expected coefficient value for interaction term: Null
- Sample: Default

19. Subfield > Methodological emphasis in multi-method research (combining quantitative and qualitative methods)

- H19: Articles in the AP subfield based on multi-method research (combining quantitative and qualitative methods) are more likely to tend towards quantitative methods, whereas CP and IR are not (Pierson 2007).
- Dependent variable: Tendency towards quantitative methods, where 1 indicates that the article’s multi-methods analysis relies on quantitative methods to a greater extent than qualitative methods, and 0 indicates that it does not.
- Independent variable: Subfield, with multinomial estimates for AP, CP, IR, PT, Conceptualization and Measurement, and Methodology.
- Estimation strategy: OLS, probit
- Expected coefficient value: For AP, positive; for CP and IR, null.
- Sample: The subset of all articles that use a combination of quantitative and qualitative methods.

20. Top cross-subfield journals <> Quantitative methods, exclusively or in tandem with other methods

- H20: Articles published in top cross-subfield journals are more likely to use quantitative methods, exclusively or in tandem with other methods, than articles published in other journals (Bennett et al. 2003).
- Variable 1: Use of quantitative methods, exclusively or in tandem with other methods. See models associated with H9.
- Variable 2: Publication in top cross-subfield journals, as defined by articles published in APSR, AJPS, or JOP. See models associated with H4.
- Estimation strategy: Pearson’s *r*
- Expected coefficient value: Positive
- Sample: Default

21. Top cross-subfield journals <> Causal identification strategy

- H20: Articles published in top cross-subfield journals are more likely to use causal identification strategies than articles published in other journals (Clark and Golder 2015).
- Variable 1: Use of causal identification strategies, including the three separate measures discussed above in reference to the models associated with H11.

- Variable 2: Publication in top cross-subfield journals, as defined by articles published in APSR, AJPS, or JOP. See models associated with H4.
- Estimation strategy: Pearson's *r*
- Expected coefficient value: Positive
- Sample: Default

22. Author-generated data <> Quantitative methods, exclusively or in tandem with other methods

- H22: Articles that employ only pre-existing (non-author-generated) data are more likely to use quantitative methods, exclusively or in tandem with other methods, than other methods.
- Variable 1: Use of quantitative methods, exclusively or in tandem with other methods. See models associated with H9.
- Variable 2: Use of author-generated data, where 1 indicates that the article relies on some form of author-generated data, and 0 indicates that it does not.
- Estimation strategy: Pearson's *r*
- Expected coefficient value: Positive
- Sample: Default

23. Author-generated data <> Qualitative methods, exclusively or in tandem with other methods

- H23: Articles that employ author-generated data are more likely to use qualitative methods, exclusively or in tandem with other methods, than other methods.
- Variable 1: Use of qualitative methods, exclusively or in tandem with other methods. See models associated with H8.
- Variable 2: Use of author-generated data, where 1 indicates that the article relies on some form of author-generated data, and 0 indicates that it does not.
- Estimation strategy: Pearson's *r*
- Expected coefficient value: Positive
- Sample: Default

24. Subfield > Policy recommendations[5]

- H24: Articles in the AP subfield are more likely to make policy recommendations than articles in other subfields.
- Dependent variable: Reference to policy recommendations, where 1 indicates that the article makes a policy recommendation, and 0 indicates that it does not.
- Independent variable: Subfield, with multinomial estimates for AP, CP, IR, PT, Conceptualization and Measurement, and Methodology.
- Estimation strategy: OLS, probit
- Expected coefficient value: For AP, positive; for all other subfields, null.
- Sample: Default

25. Time > Policy recommendations

[5] For the "Policy recommendations" analyses in (24), (25), and (26), we also present the count and proportion of articles that make policy recommendations. To calculate the proportion of articles, we divide the count of all articles that make policy recommendations by the total number of articles in the sample.

- H25: The number of articles that make policy recommendations has decreased over time (Sigelman 2006; Bennett and Ikenberry 2006; Avey and Desch 2014).
- Dependent variable: Reference to policy recommendations. See models associated with H24.
- Independent variable, version 1: Year, as an interval value.
- Independent variable, version 2: Year, as a multinomial estimate.
- Estimation strategy: OLS, probit
- Expected coefficient value: Negative
- Sample: Default

26. Post-9/11 attacks > Policy recommendations

- H26: The number of articles that make policy recommendations increased between 2002 and 2008 and then decreased for the rest of the time period of study (Maliniak et al. 2011).
- Dependent variable: Reference to policy recommendations. See models associated with H24.
- Independent variable: Year, as a multinomial estimate.
- Estimation strategy: OLS, probit
- Expected coefficient value: Positive from 2002 - 2008, negative from 2009 - 2018.
- Sample: Default

27. Subfield emphasis of journal <> Policy recommendations

- H27: Journals in the IR subfield publish more articles that make policy recommendations than other journals (Jentleson and Ratner 2011).
- Variable 1: Reference to policy recommendations. See models associated with H24.
- Variable 2: Publication in IR subfield journals, as defined by articles published in IO, ISQ, or WP. For this variable, 1 indicates that the journal is associated with the IR subfield, and 0 indicates that it is not.
- Estimation strategy: Pearson's r
- Expected coefficient value: Positive
- Sample: Default

In addition to these pre-registered analyses, we also conducted non-pre-registered analyses to explore the following relationships: (1) changes in the use of multi- (quantitative and qualitative) method research over time; (2) changes in the use of formal modeling methods over time; (3) changes in the use of all methods overtime; (4) changes in the use of non-formal modeling methods overtime; (5) the distribution of methods across each journal; (6) the relationship between quantitative methods and the gender identity of authors, exclusively or in tandem with other methods; (7) the distribution of observational and experimental methods across articles in the sample; (8) the number of articles that rely on data gathered from non-experimental sources; (9) the number of articles that rely on both pre-existing data and data gathered using experimental methods; (10) correlations between different methods of data collection and different methods of data analysis.

Section 5: Analysis of relationships between author educational backgrounds and article parameters

Notes on the sample
We restrict the analyses that we discuss below to exclude articles that we coded as associated with the Political Theory subfield and having "No discernible method" or that were associated with a PhD outside of political science. In describing the analyses below, we use "PS PhD" to indicate this subset sample. We subset subsequent samples on the basis of this PS PhD sample.

28. Seniority > Publishing volume

- H28: Graduate students and junior scholars publish less in the top journals than senior scholars.
- Dependent variable: Number of articles published by author
- Independent variable: Scholar is a grad student or junior scholar where 1 indicates the author is a grad student (PUByear - PhDyear ≤ 0) or junior scholar ($0 <$ PUByear - PhDyear < 7), and 0 indicates the author is not.
- Estimation strategy: OLS
- Expected coefficient value: Negative
- Sample: PS PhD

29a. Seniority > Authorship structure

- H29a: Status as a graduate student decreases the likelihood of authoring alone.
- Dependent variable: Solo authored article where 1 indicates the author has at least one solo authored article and 0 indicates the author does not have a solo authored article
- Independent variable: Author is a graduate student (PUByear - PhDyear ≤ 0), where 1 indicates the author is a graduate student and 0 indicates the author is not.
- Estimation strategy: OLS, probit
- Expected coefficient value: Negative
- Sample: PS PhD

29b. Seniority > Authorship structure

- H29b: Status as a junior scholar increases the likelihood of authoring alone.
- Dependent variable: Solo authored article where 1 indicates the author has at least one solo authored article and 0 indicates the author does not have a solo authored article
- Independent variable: Author is a junior scholar, where 1 indicates the author is a junior scholar and 0 indicates the author is not.
- Estimation strategy: OLS, probit
- Expected coefficient value: Negative
- Sample: PS PhD

30. Seniority > Causal identification strategy

- H30: Articles authored by graduate students/junior scholars or teams with graduate students/junior scholars are more likely to use methods that address the problem of causal inference than articles solo or co-authored by senior scholars.

- Dependent variable: Use of causal identification strategies. We test this hypothesis using three separate measures, as follows; for each, 1 indicates that the article uses the listed methods of data collection or analysis, and 0 indicates that it does not:
    - Model 30a: The use of statistics with an identification strategy or experimental data collection methods;
    - Model 30b: The use of statistics with an identification strategy, regression involving fixed effects, or experimental data collection methods; and
    - Model 30c: The use of statistics with an identification strategy, regression involving fixed effects, qualitative process tracing methods, or experimental data collection methods
- Independent variable: Presence of a graduate student or junior scholar (six or fewer years between publication and date of PhD), where 1 indicates the team of authors includes a graduate student or junior scholar, and 0 indicates it does not.
- Estimation strategy: OLS, probit. We estimate separate models for each dependent variable.
- Expected coefficient value: Positive
- Sample: PS PhD

31. PhD granted after 2012 > Multi-method research (combining quantitative and qualitative methods)

- H31: Articles authored by one or more scholars who received their PhD during the qualitative renaissance are more likely to multi-method research (combining quantitative and qualitative methods)
- Dependent variable: Use of both quantitative and qualitative methods, where 1 indicates that the articles uses a combination of quantitative and qualitative methods, and 0 indicates that it does not.
- Independent variable: PhD granted post-2012, where 1 indicates that the author or at least one member of the team of authors was granted a PhD in 2012 or later, or is currently a graduate student and 0 indicates the author/team was not.
- Estimation strategy: OLS, probit
- Expected coefficient value: Positive
- Sample: Default

32. PhD granted after 2012 > Explicit qualitative methods

- H32: Articles authored by one or more scholars who received their PhD after the qualitative renaissance are more likely to use explicit qualitative methods
- Dependent variable: Use of "explicit" qualitative methods, exclusively or in tandem with other methods, where 1 indicates that the article uses (1) process tracing; (2) structured case comparison; (3) QCA; (4) congruence analysis; and / or (5) counterfactual analysis, and 0 indicates that it does not.
- Independent variable: PhD granted post-2012, where 1 indicates that the author or at least one member of the team of authors was granted a PhD in 2012 or later, or is currently a graduate student and 0 indicates the author/team was not
- Estimation strategy: OLS, probit
- Expected coefficient value: Positive

- Sample: The subset of all articles that use qualitative methods.

Works cited

American Political Science Association Task Force on Political Science in the 21st Century. 2011. "Political Science in the 21st Century." Washington, DC: American Political Science Association. https://web.apsanet.org/21st-century/.

Avey, Paul C., and Michael C. Desch. 2014. "What Do Policymakers Want From Us? Results of a Survey of Current and Former Senior National Security Decision Makers." International Studies Quarterly 58 (2): 227–46. https://doi.org/10.1111/isqu.12111.

Bennett, Andre, Aharo Barth, and Kenneth R. Rutherford. 2003. "Do We Preach What We Practice? A Survey of Methods in Political Science Journals and Curricula." PS: Political Science & Politics 36 (3): 373–78. https://doi.org/10.1017/S1049096503002476.

Bennett, Andrew, and G. John Ikenberry. 2006. "The Review's Evolving Relevance for U.S. Foreign Policy 1906–2006." American Political Science Review 100 (4): 651–58. https://doi.org/10.1017/S000305540606254X.

Blanchard, Philippe, Benoît Rihoux, and Priscilla Álamos-Concha. 2017. "Comprehensively Mapping Political Science Methods: An Instructors' Survey." International Journal of Social Research Methodology 20 (2): 209–24. https://doi.org/10.1080/13645579.2015.1129128.

Clark, William Roberts, and Matt Golder. 2015. "Big Data, Causal Inference, and Formal Theory: Contradictory Trends in Political Science?: Introduction." PS: Political Science & Politics 48 (1): 65–70. https://doi.org/10.1017/S1049096514001759.

Collier, David, and Henry E. Brady. 2004. Rethinking Social Inquiry: Diverse Tools, Shared Standards. Lanham, Md: Rowman & Littlefield Publishers.

Druckman, James N., Donald P. Green, James H. Kuklinski, and Arthur Lupia. 2006. "The Growth and Development of Experimental Research in Political Science." American Political Science Review 100 (4): 627–35. https://doi.org/10.1017/S0003055406062514.

Emmons, Cassandra V., and Andrew M. Moravcsik. 2020. "Graduate Qualitative Methods Training in Political Science: A Disciplinary Crisis." PS: Political Science & Politics 53 (2): 258–64. https://doi.org/10.1017/S1049096519001719.

Evans, Heather K., and A. Moulder. 2011. "Reflecting on a Decade of Women's Publications in Four Top Political Science Journals." PS: Political Science & Politics 44 (4): 793–98. https://doi.org/10.1017/S1049096511001296.

Garand, James C., Micheal W. Giles, André Blais, and Iain McLean. 2009. "Political Science Journals in Comparative Perspective: Evaluating Scholarly Journals in the United States, Canada, and the United Kingdom." PS: Political Science & Politics 42 (04): 695–717. https://doi.org/10.1017/S1049096509990205.

Gerring, John. 2011. Social Science Methodology: A Unified Framework. 2nd edition. Cambridge ; New York: Cambridge University Press.

George, Alexander L., and Andrew Bennett. 2005. Case Studies and Theory Development in the Social Sciences. MIT Press.

Giles, Micheal W., and James C. Garand. 2007. “Ranking Political Science Journals: Reputational and Citational Approaches.” PS: Political Science & Politics 40 (04): 741–51. https://doi.org/10.1017/S1049096507071181.

Goertz, Gary, and James Mahoney. 2012. A Tale of Two Cultures: Qualitative and Quantitative Research in the Social Sciences. Princeton University Press.

Imai, Kosuke. 2011. “Introduction to the Virtual Issue: Past and Future Research Agenda on Causal Inference.” Political Analysis 19 (V2): 1–4. https://doi.org/10.1017/S104719870001425X.

Jentleson, Bruce W., and Ely Ratner. 2011. “Bridging the Beltway–Ivory Tower Gap.” International Studies Review 13 (1): 6–11. https://doi.org/10.1111/j.1468-2486.2010.00992.x.

Kapiszewski, Diana, Lauren M. MacLean, and Benjamin L. Read. 2015. Field Research in Political Science: Practices and Principles. Cambridge University Press.

Levy, Jack S. 2007. “Qualitative Methods and Cross-Method Dialogue in Political Science.” Comparative Political Studies 40 (2): 196–214. https://doi.org/10.1177/0010414006296348.

Little, Andrew T., and Thomas B. Pepinsky. 2016. “Simple and Formal Models in Comparative Politics.” Chinese Political Science Review 1 (3): 425–47. https://doi.org/10.1007/s41111-016-0032-0.

Lupu, Noam, and Kristin Michelitch. 2018. “Advances in Survey Methods for the Developing World.” Annual Review of Political Science 21 (1): 195–214. https://doi.org/10.1146/annurev-polisci-052115-021432.

Maliniak, Daniel, Amy Oakes, Susan Peterson, and Michael J. Tierney. 2011. “International Relations in the US Academy.” International Studies Quarterly 55 (2): 437–64.

Morgan, Kimberly J. 2016. “Process Tracing and the Causal Identification Revolution.” New Political Economy 21 (5): 489–92. https://doi.org/10.1080/13563467.2016.1201804.

Pierson, Paul. 2007. “The Costs of Marginalization: Qualitative Methods in the Study of American Politics.” Comparative Political Studies 40 (2): 146–69. https://doi.org/10.1177/0010414006296347.

Shames, Shauna L., and Tess Wise. 2017. “Gender, Diversity, and Methods in Political Science: A Theory of Selection and Survival Biases.” PS: Political Science & Politics 50 (3): 811–23. https://doi.org/10.1017/S104909651700066X.

Sigelman, Lee. 2006. “The Coevolution of American Political Science and the ‘American Political Science Review.’” The American Political Science Review 100 (4): 17.

Teele, Dawn Langan, and Kathleen Thelen. 2017. “Gender in the Journals: Publication Patterns in Political Science.” PS: Political Science & Politics 50 (02): 433–47. https://doi.org/10.1017/S1049096516002985.