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Chapter 1 : How to Identify Independent & Dependent Variables in the Study of Political Science | The Clas

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Synthetic population dataset Several of the adjustment approaches used in this study require a dataset that is highly representative of the U. This dataset essentially serves as a reference for making the survey at hand e. When selecting a population dataset, researchers typically use a large, federal benchmark dataset such as the American Community Survey ACS or Current Population Survey CPS , as those surveys have high response rates, high population coverage rates and rigorous probability-based sample designs. One limitation of using a single survey, such as the ACS, is that the only variables that can be used in adjustment are those measured in the ACS. This means that a researcher could adjust on characteristics like age, income and education but not political party affiliation, religious affiliation or voter registration. One solution is to take several benchmark datasets measuring somewhat different variables and combine them to create a synthetic population dataset. The subsequent sections detail how the synthetic population dataset was constructed for this study. Construction of the synthetic population dataset The synthetic population dataset was constructed in three main steps: Researchers downloaded public use datasets for nine benchmark surveys and then recoded common variables e. These 20, case datasets were then combined into a single large dataset. Using that combined dataset, researchers produced 25 multiply imputed datasets via the chained equations approach. After imputation, only the 20, cases that originated from the ACS were kept, and all others were discarded. This was done to ensure that the distribution of the main demographic variables precisely matched the ACS distribution, while the imputed variables reflect the distribution that would be expected based on the ACS demographic profile. Each of these steps is discussed in detail below. Dataset selection and recoding Nine datasets were used to construct the synthetic population dataset: Each survey contributed a number of variables to the frame. In all, the frame contains 37 variables, with many of these variables present in multiple surveys. All nine datasets featured a number of common demographic variables such as sex, age, race and Hispanic ethnicity, education, census division, marital status, household size, number of children, U. Other variables were only measured in a subset of the surveys. Variables that were measured or coded differently across surveys were recoded to be as comparable as possible. This often meant that variables were coarsened. For example, the CPS top-codes age at 85 years or more, so the same coding scheme was applied to all of the other surveys as well. In other cases, this involved treating inconsistent values as missing. However, the CPS surveys also allow respondents to indicate that the number of hours they usually work per week varies, while the ACS does not have this option. In the above table, missing data for hours worked per week across the CPS surveys is not truly missing; rather, it consists of people who indicated that their hours vary. However, these data are treated as missing for consistency with the way it is asked in the ACS. Imputed values can be interpreted as predicting how those individuals would have answered if they had been asked the ACS question instead. Stratified sampling The benchmark datasets differed in sample design and sample sizes. In order to address these differences, we selected exactly 20, observations per dataset before appending them together. The sample size was selected in order to provide enough data for the adjustment methods used while still being computationally tractable. We used the relevant weights for each dataset. The CPS Internet Supplement was filtered down to respondents who had a random respondent weight, because the texting and social networking variables were only measured for these respondents. The nonresponse weight was used for the CPS Volunteer Supplement, while the nonresponse weight accounting for both cross-section and panel cases was used for the GSS. Each of these weights was rescaled to sum to the sample size of each of their respective datasets. This entire procedure is also repeated 25 times, independently of one another, to produce multiple synthetic frames that can be compared against one another to assess variance stemming from the imputation process. Each frame went through 10 iterations. This ensures that the demographic distribution closely matches that of the original ACS, while the imputed variables reflect the joint distribution that would be expected based on the variables that each dataset had in common. Evaluating the imputation quality We took several steps to ensure that the imputation procedure produced results that accurately reflected the original datasets. First, we crossed each of the imputed variables e. Overall, the imputed distributions were quite close to the originals. The average absolute difference between the imputed and original values for each cross-classification was 2 percentage points. This means that on average, the imputed values not only matched the distribution for the full population, but also matched the distribution within demographic subgroups. Although the multiple imputation procedure created 25 versions of the synthetic population dataset, only one of them was used to perform the adjustments in this study. One concern with this approach is the possibility that the results could vary widely depending on which of the 25 synthetic populations was used. For each substantive category in the 24 benchmark variables, we calculated the weighted percentage for each bootstrapped sample. Then we calculated the total variance mean squared error for each estimate with all 25, bootstrap samples combined. Finally, we calculated the variance for each of the 25 sets of estimates separately and took the average. This is the within-imputation variance. This process was repeated for all three vendors. If the total variance is much larger than the within-imputation variance, then estimated variability and margins of error that use only a single imputation as was done in this study would be underestimated. In this case, the total variance was only 1. This means that the estimated variability described in the report is for all practical purposes the same as if the analysis had been repeated for all 25 imputations. The reason the two are so close is likely due to the fact the imputation only affects the variability of the survey estimates indirectly, and makes up only a small portion of the survey variability. If we were to compare the total and within-imputation variability for the imputed values themselves as we might if the synthetic population dataset were the main focus of the analysis rather than simply an input to the weighting , the difference would likely be larger. Adjustment variables used in the study The core demographic adjustment variables used in the study were 6-category age, sex, 5-category educational attainment, race and Hispanic ethnicity, and census division. The expanded political variables add to this 3-category political party affiliation, 3-category political ideology, voter registration, and whether the respondent identifies as an evangelical Christian. The following table compares the distribution of the adjustment variables on the synthetic population dataset versus from one of the original high-quality survey datasets used to create the synthetic dataset. All demographic variables were fully observed on the ACS, so the synthetic frame will differ from the original source only on the set of expanded political variables. The largest difference between the source survey and the synthetic frame was on political ideology. The exact reason for this discrepancy is unclear, but there are several potential factors. Finally, there may be important differences between the demographic makeup of respondents to the GSS and respondents to the ACS. Douglas Rivers and Delia Bailey. Stuart, Constantine Frangakis, and Philip J. Multiple Imputation by Chained Equations. Van Buuren, and E.

Chapter 2 : Appendix B: Synthetic population dataset | Pew Research Center

Ten Myths About Women and Politics. Sex and politics have been an explosive combination ever since women won the right to vote. When the League of Women Voters was established in in the final days of the fight for women's suffrage, the St. Louis Globe Democrat wrote that war between the sexes had all but been declared (Mueller,).

The subsample sizes ranged from 2, to 8, in increments of Therefore, to simplify reporting, the results presented in this study are averaged across the three samples. How we combined multiple surveys to create a synthetic model of the population Often researchers would like to weight data using population targets that come from multiple sources. Census Bureau, provides high-quality measures of demographics. For some methods, such as raking, this does not present a problem, because they only require summary measures of the population distribution. But other techniques, such as matching or propensity weighting, require a case-level dataset that contains all of the adjustment variables. This is a problem if the variables come from different surveys. Next, we took the data for these questions from the different benchmark datasets e. Some of the questions â€" such as age, sex, race or state â€" were available on all of the benchmark surveys, but others have large holes with missing data for cases that come from surveys where they were not asked. The next step was to statistically fill the holes of this large but incomplete dataset. For example, all the records from the ACS were missing voter registration, which that survey does not measure. We used a technique called multiple imputation by chained equations MICE to fill in such missing information. This process is repeated many times, with the model getting more accurate with each iteration. Eventually, all of the cases will have complete data for all of the variables used in the procedure, with the imputed variables following the same multivariate distribution as the surveys where they were actually measured. The result is a large, case-level dataset that contains all the necessary adjustment variables. For this study, this dataset was then filtered down to only those cases from the ACS. This way, the demographic distribution exactly matches that of the ACS, and the other variables have the values that would be expected given that specific demographic distribution. This synthetic population dataset was used to perform the matching and the propensity weighting. It was also used as the source for the population distributions used in raking. This approach ensured that all of the weighted survey estimates in the study were based on the same population information. See Appendix B for complete details on the procedure. Raking For public opinion surveys, the most prevalent method for weighting is iterative proportional fitting, more commonly referred to as raking. With raking, a researcher chooses a set of variables where the population distribution is known, and the procedure iteratively adjusts the weight for each case until the sample distribution aligns with the population for those variables. The process will adjust the weights so that gender ratio for the weighted survey sample matches the desired population distribution. Next, the weights are adjusted so that the education groups are in the correct proportion. If the adjustment for education pushes the sex distribution out of alignment, then the weights are adjusted again so that men and women are represented in the desired proportion. The process is repeated until the weighted distribution of all of the weighting variables matches their specified targets. Raking is popular because it is relatively simple to implement, and it only requires knowing the marginal proportions for each variable used in weighting. That is, it is possible to weight on sex, age, education, race and geographic region separately without having to first know the population proportion for every combination of characteristics e. Raking is the standard weighting method used by Pew Research Center and many other public pollsters. In this study, the weighting variables were raked according to their marginal distributions, as well as by two-way cross-classifications for each pair of demographic variables age, sex, race and ethnicity, education, and region. Matching Matching is another technique that has been proposed as a means of adjusting online opt-in samples. It involves starting with a sample of cases i. In this study, the target samples were selected from our synthetic population dataset, but in practice they could come from other high-quality data sources containing the desired variables. Then, each case in the target sample is paired with the most similar case from the online opt-in sample. When the closest match has been found for all of the cases in the target sample, any unmatched cases from the online opt-in sample are discarded. If all goes well, the remaining matched cases should be a set that closely resembles the target population. However, there is always a risk that there will be cases in the target sample with no good match in the survey data â€” instances where the most similar case has very little in common with the target. If there are many such cases, a matched sample may not look much like the target population in the end. There are a variety of ways both to measure the similarity between individual cases and to perform the matching itself. To perform the matching, we temporarily combined the target sample and the online opt-in survey data into a single dataset. The kind of model used was a machine learning procedure called a random forest. Random forests can incorporate a large number of weighting variables and can find complicated relationships between adjustment variables that a researcher may not be aware of in advance. In addition to estimating the probability that each case belongs to either the target sample or the survey, random forests also produce a measure of the similarity between each case and every other case. The random forest similarity measure accounts for how many characteristics two cases have in common e. The final matched sample is selected by sequentially matching each of the 1, cases in the target sample to the most similar case in the online opt-in survey dataset. Every subsequent match is restricted to those cases that have not been matched previously. Once the 1, best matches have been identified, the remaining survey cases are discarded. In simulations that started with a sample of 2, cases, 1, cases were matched and were discarded. Similarly, for simulations starting with 8, cases, 6, were discarded. In practice, this would be very wasteful. However, in this case, it enabled us to hold the size of the final matched dataset constant and measure how the effectiveness of matching changes when a larger share of cases is discarded. The larger the starting sample, the more potential matches there are for each case in the target sample â€” and, hopefully, the lower the chances of poor-quality matches. Propensity weighting A key concept in probability-based sampling is that if survey respondents have different probabilities of selection, weighting each case by the inverse of its probability of selection removes any bias that might result from having different kinds of people represented in the wrong proportion. The same principle applies to online opt-in samples. The only difference is that for probability-based surveys, the selection probabilities are known from the sample design, while for opt-in surveys they are unknown and can only be estimated. As with matching, random forests were used to calculate these probabilities, but this can also be done with other kinds of models, such as logistic regression. Cases with a low probability of being from the online opt-in sample were underrepresented relative to their share of the population and received large weights. Cases with a high probability were overrepresented and received lower weights. As with matching, the use of a random forest model should mean that interactions or complex relationships in the data are automatically detected and accounted for in the weights. However, unlike matching, none of the cases are thrown away. A potential disadvantage of the propensity approach is the possibility of highly variable weights, which can lead to greater variability for estimates e. Combinations of adjustments Some studies have found that a first stage of adjustment using matching or propensity weighting followed by a second stage of adjustment using raking can be more effective in reducing bias than any single method applied on its own. Following up with raking may keep those relationships in place while bringing the sample fully into alignment with the population margins. These procedures work by using the output from earlier stages as the input to later stages. The propensity model is then fit to these 3, cases, and the resulting scores are used to create weights for the matched cases. When survey respondents are self-selected, there is a risk that the resulting sample may differ from the population in ways that bias survey estimates. This is known as selection bias, and it occurs when the kinds of people who choose to participate are systematically different from those who do not on the survey outcomes. Selection bias can occur in both probability-based surveys in the form of nonresponse as well as online opt-in surveys. Lavrakas and Victor Lange. For samples where vendors provided their own weights, the set of weights that resulted in the lowest average bias was used in the analysis. For this study, a minimum of 2, was chosen so that it would be possible to have 1, cases left after performing matching, which involves discarding a portion of the completed interviews. This enabled us to measure the amount of variability introduced by each procedure and distinguish between systematic and random differences in the resulting estimates. Stuart, Constantine Frangakis, and Philip J. Multiple Imputation by Chained Equations. A Review and a Look Forward.

Chapter 3 : Do the variables politics and sex appear to be independent

Janet A. Flammang, "Sex as a Political Variable: Women as Candidates and Voters in U.S. calendrierdelascience.comd A. Seltzer, Jody Newman, Melissa Voorhees Leighton Gender Dynamics in Congressional Elections.

As a term it is used to refer to a wide range of phenomena, stemming from multiple and even competing meanings of gender and politics. Its definition is further complicated by the emergence of similar and related phrases like women and politics, gender and politics, and the politics of gender. This complexity indicates ongoing conceptual debates within research on gender and politics. At the same time, it reflects theoretical and empirical developments as the study of gender politics has evolved and grown to encompass a broad and heterogeneous set of topics. At the most basic level, it is crucial to distinguish between sex, gender, and sexuality. In their most common usages, sex denotes biological differences between men and women as male and female, gender describes the social meanings given to sexual differences through notions of masculine and feminine, and sexuality refers to sexual relations and questions of sexual orientation. However, definitions of all three of these terms, as well as the connections between them, are subject to a great deal of confusion and debate. First, there is a tendency to identify all three terms with only one side of the dichotomies they represent: The result is that sex and gender are often treated as synonymous with women, while sexuality is considered only in relation to gays, lesbians, bisexuals, transsexuals, and transgendered individuals. Second, there are important disagreements on the ways in which sex, gender, and sexuality inform and are linked to one another. Although the binaries of sex and gender assume heterosexuality, for example, other sexual orientations raise questions about the necessary connections between male and masculine and female and feminine. These patterns intersect with debates about the causal relations between these terms: Although some argue that sex produces gender which leads to sexuality, others suggest that gender and compulsory heterosexual-ity give rise to distinctions on the basis of sex. Parallel to these discussions, feminists and others have pioneered new uses for the term politics. Although many people employ this word to refer to formal political processes, like government and elections, politics has assumed at least two additional meanings in the last several decades. They insist that social movements are a form of political participation on a par with engagement inside the state. At the same time, they draw attention to the power relations that permeate all levels of social life, including relations within the private sphere of home and family. For them, "the personal is political. They are thus interested not only in the politics of the state and the politics of social movements, but also in the politics of language, the politics of exchange, and the politics of representation, to give but a few examples. These debates, in turn, lead to a range of different understandings of the term gender politics and cause it to be confused with related terms like women and politics, gender and politics, and the politics of gender. Although many people use these phrases interchangeably, it is possibleâ€"on the basis of the theoretical distinctions outlined aboveâ€"to carve out some general differences between them. Gender and politics covers many of these same topics, but in addition, implies attention to masculinities and femininities, as well as relations between men and women, as they operate in various political arenas. The politics of gender, finally, comprises a closer look at the power relations behind definitions ofâ€"and presumed causal relations betweenâ€"sex, gender, and sexuality. In comparison, gender politics may refer to any and all of these distinct foci of investigation. Individual disciplines take up the study of gender politics in various ways, depending on their core research interests and theoretical frameworks. Because various currents in sociology, anthropology, and philosophy embrace broad definitions of politics, scholars in these fields use the term gender politics in many different ways to refer to the study of women and politics, gender and politics, and the politics of gender. Ironically, political scientists tend to adopt a much narrower definition of gender politics to refer only to the study of women and politics and gender and politics, where the term politics encompasses only formal and informal political processes, to the exclusion of questions about broader power relations. Even this more restricted focus, however, has produced a wide range of literature that over time has expanded and evolved in terms of theoretical approaches and fields of empirical research. APPROACHES As feminist theorists have developed sex and gender as analytical categories, scholars in political science have elaborated a series of approaches for analyzing the sexed and gendered nature of political life. It was thus guided by an "add women and stir" approach: Using sex and gender as synonyms for women, it sought to include women but did not question the male norm implicit in reigning understandings of political processes. Recognizing the limits of this approach, the second phase shifted its attention to the activities of women as women and analyzed their participation in formal and informal politics. Although many scholars continued to employ the term gender when they discussed only women, a growing number also began to use it to refer to relations between men and women in order to study how the form and content of politics reflect and shape inequalities. The third and current phase extends these insights to explore how ideas about sex and gender permeate all aspects of political life, sometimesâ€"but not alwaysâ€"with the intent to break down these dichotomies. This work introduces, for the first time, the importance of studying masculinities as well as femininities in politics. It also investigates how political science itself may be gendered in terms of its concepts, definitions, theories, and methods. The main theoretical innovation that emerges over the course of these stages is a multifaceted shift in focus from sex to gender. In light of the different definitions attributed to these terms, analysts ascribe at least three distinct meanings to this shift. The first is a move away from biological sex, or the notion that men and women are binary opposites, toward socially constructed gender identities, or the idea that masculinity and femininity constitute features that exist along a continuum. The second is a move away from exclusive concern with women in politics and public policy toward greater attention to the impact of masculinities and femininities, as well as relations between men and women, on political inputs and outcomes. The third is a move away from sex as one of many possible variables in political science toward gender as a concept that forces a fundamental reexamination of core features of political life. All three aspects of the shift from sex to gender, nonetheless, are in some sense incomplete. For one, mainstream and feminist researchers find that while indicators for sex are relatively straightforward to incorporate into political analysis, those for gender are much more complicated. This is partly because sex refers to biological markers that are relatively unambiguous, while gender denotes social meanings that may vary a great deal within and across particular contexts. However, this is also due to difficulties that many people experience in grasping that the relationship between sex and gender is not a perfect one. Secondly, many feminists are hesitant to abandon sex in favor of gender. As the two concepts are not equivalent, these scholars argue that both are crucial to good research design, whether the purpose is to analyze men and women or masculinities and femininities as these play out in various kinds of political arenas. Seeking to break down dichotomies of public versus private spheres and formal versus informal politics, these scholars have explored the effects of sex and gender on a broad range of political activities. Turning to the products of political processes, gender politics researchers have theorized the role of the state in reflecting and shaping gender relations. They analyze how states contribute to the reproduction of gender hierarchies, or alternatively, lead to changes in patterns of inequality through different kinds of public policies. The possibilities of exploring other definitions of politics and incorporating interactions with other identities, combined with the already multifaceted nature of sex and gender, ensure that all six of these areas will remain vibrant areas for future research.

Chapter 4 : POLITICS, GENDER (Social Science)

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Chapter 5 : How different weighting methods work | Pew Research Center

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