**ONLINE APPENDIX: VOTER RESPONSE TO SALIENT JUDICIAL DECISIONS IN RETENTION ELECTIONS**

**Data and Sources**

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| **Variable** | **Data Source** |
| VEP | United States Election Project |
| %VEP voting in top ballot race | United States Election Project |
| Judicial retention election results | State records |
| Rep. vote share | State records; The American Presidency Project (UC Santa Barbara) |
| State-level demographic data | US Census |
| State unemployment rate | Bureau of Labor Statistics |
| Religious adherence data | Association of Religion Data Archives |



Gaps in Turnout Between Iowa and Synthetic Iowa: 1984-2010.

Note: Vertical line at 2008 election prior to *Varnum* decision.



Gaps in Retention Race “No” Votes Between Iowa and Synthetic Iowa: 1984-2010.

Note: Vertical line at 2008 election prior to *Varnum* decision.



Placebo Tests: “No” Vote Analyses for Each Comparison State.

Note: Vertical lines at 2008 election prior to *Varnum* decision.



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Placebo Tests: “No” Vote Analyses for Each Comparison State.

Note: Vertical line at 2008 election prior to *Varnum* decision.



Gaps in Retention Race Participation Between Iowa and Synthetic Iowa: 1984-2010.

Note: Vertical line at 2008 election prior to *Varnum* decision.



Retention Race Participation in Iowa Compared to Comparison States Mean: 1984-2010.

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Retention Race Participation in Iowa Compared to Comparison States Mean: 1984-2010.

Note: Roll-off is measured as the proportion of voters who cast a ballot in the top-ballot race but do not cast a ballot in the judicial retention race.

**Difference-in-Differences Estimation**

Difference-in-differences estimation is an approach to estimating the effect of an event on an outcome of interest. This type of analysis is one way for researchers to imagine groups exposed to an intervention (such as a policy change) as being in a treatment group and those not exposed to an event as being in a control group. In the main example presented in the paper, the intervention or treatment, is the Iowa Supreme Court’s *Varnum v. Brien* decision; Iowa—the state where the court legalized same-sex marriage—is the treatment group and the other states in the data set are the control group.

After hypothesizing the potential effect of the intervention, researchers then compare the change in the outcome of interest after the intervention in the treatment group with the change in the outcome during the same period in the control group. The outcomes, or outcome/dependent variables, in the Iowa case presented in the paper are general election turnout, negative votes in the judicial retention race, and judicial retention race participation. The analyses in the paper evaluate the hypothesized effect of *Varnum* on each of these outcomes by comparing the change in those outcomes after *Varnum* in Iowa with the change in the average of those outcomes after *Varnum* in the comparison states. This approach is preferable to simply comparing the post-intervention outcomes of the treatment and control groups, as those outcomes might reflect other differences between the two groups that are unrelated to the *Varnum* decision.

The typical way to estimate the difference in the differences of the outcomes between the two groups is to calculate the difference between the pre- and post-intervention outcome means for each group (treatment and control) and then to calculate the difference between the treatment group’s difference in means and the control group’s difference in means. This difference between the two differences is then assumed to be an estimate of the treatment effect of the intervention.

Researchers often use regression analysis to analyze the relationship between an independent and a dependent variable when controlling for variables that might measure other factors affecting the relationship. In ordinary least squares (OLS) regression, the coefficient of each independent variable represents the effect on the dependent variable of increasing that independent variable by one unit, when controlling for the other independent variables in the model. In the case of the Iowa example, Table 1 in the article presents the results of an OLS regression analysis of retention race participation (the dependent variable) in Iowa. The estimate of the effect of *Varnum* on retention race participation—the difference-in-differences estimator—is the coefficient of the IA x 10 variable, which represents Iowa in 2010 after the *Varnum* decision. This coefficient suggests that after the *Varnum* decision, participation in Iowa’s state supreme court retention race increased by 12.12 percentage points. In other words, the difference between participation in Iowa’s supreme court retention race before and after *Varnum* was 12.12 percentage points greater than the difference in participation before and after the decision in the comparison states.

Another approach to difference-in-differences analysis is to create a synthetic control—a counterfactual version of the treated unit (Iowa in the main analyses in the article) that reflects what would have occurred in the absence of the treatment (*Varnum*). The synthetic control is then compared to the actual treated unit (Iowa), and the researcher attributes the difference between the two to the treatment.

To construct a synthetic control, researchers assign varying weights to the individual comparison states.[[1]](#endnote-1) The state weights are selected such that the synthetic control matches the treated unit as well as possible with respect to the values of the predictor variables (variables thought to covary with or predict the outcome variable) that are most important for predicting the outcome in the pre-treatment period (Abadie, Diamond, and Hainmueller 2010, 498).[[2]](#endnote-2) The state weights for the synthetic control are then used to calculate the outcome that we would expect for the treated unit in the absence of the treatment (*Varnum*). If the synthetic control matches the treated unit in the pre-treatment period, then the effect of the treatment is the difference between the outcome in the treated unit and the outcome in the synthetic control after treatment.

**Constructing the Synthetic Controls**

A detailed description of the non-parametric difference-in-differences method applied in the paper is provided in Abadie, Diamond, and Hainmueller (2010). It is important to note, as the authors do, that all possible weighted combinations of the comparison unit states represent potential synthetic controls. I conduct the analyses presented in the paper using the Synth package for R (Abadie, Diamond, and Hainmueller 2011). Each synthetic control presented throughout the paper is a “weighted average of potential control states, with weights chosen so that the resulting synthetic” state “best reproduces the values of a set of predictors” of the outcome variable (Abadie, Diamond and Hainmueller 2010, 498).[[3]](#endnote-3)

Each synthetic control is, therefore, a weighted combination of comparison states that is generated based on comparison states’ values of those covariates that are important for predicting the outcome in the treated state. Each comparison state is weighted to minimize the difference between the covariate values of the treated unit and the resulting synthetic control. It is for this reason that the weighted comparison states contributing to synthetic Iowa are different for each of the outcome variables. I use the R package to go through this process for each of the synthetic controls included in the article.

The data include the same set of voting predictors for all the states. I include these variables, because they represent the aggregate demographic and socioeconomic factors that most political scientists accept as common voting predictors, as well as those factors that might be important in a race where same-sex marriage is an important issue. However, the importance of each of these factors will vary across states and across outcomes. For example, race may play a more important role in determining participation in some states than others; and the factors that are important for determining overall participation in a judicial retention race may be different from those that predict negative vote shares. For these reasons, and because of the way a synthetic control is constructed, the important predictors and state weights for constructing a synthetic control will vary across analyses. To illustrate how this works further, the tables below present the predictor weights and state weights for each synthetic control included in the paper.

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| --- | --- | --- | --- |
| State- level Voting Predictor Weights for Each Outcome Variable | | | |
| State- level Voting Predictors | IA Gen. Election Turnout | IA Retention Race “No” Votes | IA Retention Race Participation | WY Retention Race Participation |
| Top Ballot Race | 0.011 | 0.000 | 0.002 | 0.076 |
| Ret. Race Participation | NA | 0.402 | NA | NA |
| Justice Term Length | 0.003 | 0.056 | 0.022 | 0.009 |
| Population | 0.040 | 0.009 | 0.048 | 0.324 |
| % Pop. White | 0.066 | 0.000 | 0.013 | 0.004 |
| % Pop. Black | 0.012 | 0.240 | 0.001 | 0.116 |
| % Pop. Hispanic | 0.000 | 0.002 | 0.084 | 0.000 |
| % Pop. Some College | 0.000 | 0.000 | 0.100 | 0.002 |
| Poverty Rate | 0.263 | 0.000 | 0.299 | 0.010 |
| Home Ownership Rate | 0.036 | 0.031 | 0.187 | 0.000 |
| % Pop. Urban | 0.001 | 0.000 | 0.018 | 0.129 |
| Median Income | 0.000 | 0.029 | 0.037 | 0.001 |
| Unemployment Rate | 0.027 | 0.000 | 0.021 | 0.206 |
| Catholic Adherence | 0.074 | 0.000 | 0.006 | 0.054 |
| Mormon Adherence | 0.060 | 0.000 | 0.135 | 0.032 |
| Religious Adherence | 0.006 | 0.170 | 0.018 | 0.029 |
| Rep. Vote Share | 0.400 | 0.061 | 0.010 | 0.008 |

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| --- | --- | --- | --- |
| Comparison State Weights for Each Outcome Variable | | | |
| Comparison States | IA Gen. Election Turnout | IA Retention Race “No” Votes | IA Retention Race Participation | WY Retention Race Participation |
| Alaska | 0.000 | 0.000 | 0.000 | 0.138 |
| Arizona | 0.000 | 0.474 | 0.000 | 0.040 |
| California | 0.000 | 0.069 | 0.000 | 0.000 |
| Colorado | 0.697 | 0.000 | 0.000 | 0.000 |
| Florida | 0.000 | 0.000 | 0.000 | 0.000 |
| Indiana | 0.000 | 0.043 | 0.644 | 0.000 |
| Iowa | NA | NA | NA | 0.530 |
| Kansas | 0.000 | 0.000 | 0.196 | 0.008 |
| Missouri | 0.000 | 0.000 | 0.000 | 0.000 |
| Oklahoma | 0.000 | 0.084 | 0.000 | 0.000 |
| South Dakota | 0.196 | 0.003 | 0.027 | 0.000 |
| Utah | 0.002 | 0.327 | 0.029 | 0.284 |
| Wyoming | 0.105 | 0.000 | 0.103 | NA |

1. Fowler (2013), for example, uses both approaches for estimating the impact of unit-level effects on electoral outcomes. [↑](#endnote-ref-1)
2. For more information on this approach and the Synth statistical package see Abadie, Diamond and Hainmueller (2010, 2011). [↑](#endnote-ref-2)
3. For more information on this approach and the Synth statistical package see Abadie, Diamond and Hainmueller (2010, 2011). [↑](#endnote-ref-3)