The Effects of State Party Control on Environmental Policy

Undergraduate Research Thesis

Presented in partial fulfillment of the requirements for graduation with *honors research distinction* in Political Science in the undergraduate colleges of The Ohio State University

By

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I. Abstract

The data suggest party control in environmental policy does matter and there has been a significant change in how environmental policy has been viewed and legislated since before 2000 to beyond 2000. Since 2000, in the state legislature across all chambers there is some evidence that Republicans create more pro-environmental energy policy, but these findings were not significant. On the other hand, Democrats create significantly more pro-environmental air quality policy. At the gubernatorial level, Democratic governors pass more pro-environmental energy and air quality policies, but especially air quality policies which were found to be significant. Pro-environmental energy and air policies are difficult to pass during divided government, but under unified government Democrats pass significantly more pro-environmental air policies and energy policies. Finally, both Republican and Democratic governors alike struggle to pass pro-environmental policy the longer they are in office which is consistent with findings from Kousser and Phillips.

II. Introduction

In state politics, a widespread reality is that the differences of party control at different branches of government can lead to drastically different policy outcomes. While many political scientists have examined this at the federal level, few have examined it at the state level, even less have looked at in terms of environmental policy, and none have examined it quite at this level of analysis. In this study, the effects of state party control, whether Democrats or Republicans control the state legislature or governorship, will be examined for their impact on environmental policy.

But why should voters or legislators even be interested in state environmental policy? Many recent articles such as one found in National Geographic describe that legislatures should enact aggressive environmental policies now because irreversible and catastrophic climate change conditions could be reached by as early as 2030. If legislatures do not enact these policies, they argue that global temperatures can rise 9 °F, sea levels could rise 20-30 feet with the melting of the Arctic cap and Antarctica's ice sheets, the world's coral reefs and the Amazon rainforest could disappear, and large parts of the planet would be uninhabitable (Leahy; 2019). Even if legislatures take aggressive action, the United Nations projects that this is merely to only limit global warming to about 2.7 °F (Emissions Gap Report 2019; 2019). For example, just meeting the baselines of the Paris Climate Accord would still rise temperatures about 5.4 °F (Leahy; 2019). In order to reach that aggressive mark of only a 2.7 °F rise in temperature, global carbon emissions would need to fall 7.6% per year from now until 2030 (Emissions Gap Report 2019; 2019). While states in the United States make up just a small percentage of the entire globe, the sum of their parts shapes what emissions will be for the country. Also, specific states like California, New York, or Texas make up significant percentages of the country's population. One state's decision could greatly impact the ability for the United Nations to reach the goal of reducing emissions by 7.6% per year.

So, what should voters or state legislators in the United States seek in order to do their part in reaching such a lofty goal? This study will analyze the policies put out by Democrats and Republican state legislatures and state governors so perhaps pro-environmental voters can choose to base their votes along partisan lines. Instead, perhaps, in the event of one party making less environmentally friendly policies, legislators can change their behaviors to reach the goal set by the UN. However, maybe partisanship does not matter in terms of environmental policy at all and it is an entirely bipartisan issue. With this information in mind, voters and legislators can improve their environmental decision-making.

III. Relevant Literature

There is minimal research on state party control. Research that has been done on it is very recent. One article "Incremental Democracy: The Policy Effects of Partisan Control on State Government" from 2017 suggests that policy effects of party control are weak and inconsistent, but Democrats do tend to have more liberal policies and this trend has doubled in magnitude in recent decades. Furthermore, the study suggests that a Democrat governor instead of a Republican governor leads to about 1% more liberal policies (Caughey, et. al; 2017).

Another article "Noisy Retrospection: The Effect of Party Control on Policy Outcomes" suggests that changing one chamber of state government (senate, house, or governor) rarely makes a difference in outcomes. Environmental policy determines that CO_2 emissions decrease with a Democratic governor or Democratic senate, but increase with a unified legislature or Democratic house. For energy consumption, electing Democrats increased consumption across the board. For energy price, there was no significant difference for any of the chambers (Dynes and Holbein; 2019).

However, broader investigations can apply to this study. Such as in "Partisanship in Perspective" that describes the sharp divide in partisanship between Democrats and Republicans. American party polarization is currently at an all-time high with party-unity scores, a measure of how frequently members vote along party lines in congressional votes, being around 90% in 2009 and only being about 70% in 1956 (Nivola; 2010). Such a divide infers large differences between the two parties and in theory that should lead to different policies enacted depending upon which party holds control of state government.

Another study "The Effects of Party and Preferences on Congressional Roll-Call Voting" shows that both partisanship and party control impact policies since party effects (voting along party lines) was highest on close votes, procedural votes, and key party issues. However, it was lowest on matters of conscience like abortion, affirmative action, and gun control (Ansolabehere; 2001). So, since party control and partisanship matter at the federal level it can be assumed that this applies to some extent at the state level as well. It will be interesting to determine if environmental policies have high party effects if, for example, it is an entirely Democratic issue or perhaps instead it is a matter of conscience and largely a bipartisan issue.

Finally, in "Understanding Policy Diffusion in the U.S.: An Information-Theoretical Approach to Unveil Connectivity Structures in Slowly Evolving Complex Systems" the study shows that in terms of public health, state legislatures often mimic or borrow policies from other states (Anderson, et. al; 2016). The study assumes that this applies to other state policies as well. So if one state were to enact a more stringent fuel efficiency standard, it can be expected that other states would begin adopting those same standards as well. With all of these studies in mind, the picture of how environmental policy impacts state party control can begin to take shape.

IV. Research Design

Party control will be viewed in three different ways: control of Governor's mansion, control of State Senate, control of State House of Representatives. While environmental policy can be measured many ways, in this study it will be measured with regards to global warming's effect on climate change. So, many clean energy policies and air quality policies have been examined and combined to form an Energy Index and an Air Index. The Air Index seeks to measure policies that fight to reduce air pollution and provide for cleaner air. The Energy Index seeks to measure policies that seek to reduce energy use and provide for cleaner and more renewable energy resources. In terms of quantity, the Air Index examines five pro-environmental policies that states often adopt, while the Energy Index examines 11 policies. Each policy is then standardized and then summed together into the index. The higher the value, the more pro-environment the state is.

According to Kousser and Phillips in state politics, it is rarely the governor that sets the agenda for what kinds of policies state legislatures should seek to pass in a given year. Unless the governor argues to pass a policy through the budget, he/she is very popular, or he/she has a partisan legislative majority; governors struggle to pass policy (Kousser and Phillips; 2012). Since the Democratic Party views themselves as the pro-environmental party, do Democratic governors affect environmental policy by passing pro-environmental legislation? Given the Kousser and Phillips model it assumes this to be unlikely. This issue examines using a regression discontinuity design with the discontinuity being winning an election. Since elections can often go either way, by looking at the close margins where either a Democrat or Republican could have won, then it can be examined if there were drastic changes in policy. In these close elections, it is easy to visualize a counterfactual of the losing candidate potentially winning instead. With this in mind, we can then treat the election result as-if random and then see what the impact is on environmental policy.

This project uses the Correlates of State Policy dataset from Michigan State University. This dataset is extensive and diverse to include many different policies and their outcomes. Unfortunately, measurements are at the state level which makes analysis difficult. The time frame used for this data set will be from 1970 - 2016 which accounts for “modern” environmental policy since the creation of the Environmental Protection Agency in 1970.

First, it must determine what hypothesis to test:

Let δ be the difference between μ_1 and μ_2 .

Let μ_1 be the air index or energy index for states with Democratic party control.

Let μ_2 be the air index or energy index for states with Republican party control.

H_0: $\delta = \mu_1 - \mu_2 = 0$ vs. H_a: $\delta = \mu_1 - \mu_2 > 0$

Optimally, a natural experiment would minimize the usage of assumptions and maximize external validity, but there is certainly a self-selection problem. If states choose for or against these policies, then they have self-selected to be in the treatment (pro-environmental policy) or control group (anti-environmental policy). This makes analysis much more complicated. Additionally, the control and treatment groups would not be considered as-if random. The model expects that most of the more liberal states would be in the treatment group, and the more conservative states would be in the control group. If there were data at the county level, this could mitigate some of the self-selection and differences between treatment and control group. This would allow for very conservative counties in the treatment group and very liberal counties in the control group which would not be possible at the state level.

Furthermore, there can be subdivision of the control and treatment groups into very liberal, slightly liberal, moderate, slightly conservative, and very conservative counties for better analysis between groups. Alas, this data does not appear to exist and so the optimal research design is not possible. Instead, using a regression-discontinuity design gives the model relatively high external validity.

Using definitions from the Correlates of State Policy dataset, the Energy Index 11 policies are and with descriptive statistics (non-standardized) created from R (Correlates of State Policy; 2019):

1. environment_bottlebill - Does the state require a deposit on bottles paid by the consumer and refunded when the consumer recycles? (dichotomous variable: 0 or 1) First enacted in a state in 1972.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1970-2016	0.000	0.000	0.000	0.165	0.000	1.000
2000-2016	0.000	0.000	0.000	0.2113	0.000	1.000

2. environment_electronic_waste – Does the state have a recycling program for electronic waste? (dichotomous variable: 0 or 1) First enacted in 2000.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1970-2016	0.000	0.000	0.000	0.1194	0.000	1.000
2000-2016	0.000	0.000	0.000	0.3301	1.000	1.000

3. environment_publicbenefit_funds – Does the state have a public benefit fund for renewable energy and energy efficiency? (dichotomous variable: 0 or 1) First enacted in 1996.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1970-2016	0.000	0.000	0.000	0.1568	0.000	1.000
2000-2016	0.000	0.000	0.000	0.3914	1.000	1.000

4. w_environment_solar_taxcredit – Does the state have a tax credit for residential solar installations? (dichotomous variable: 0 or 1) First enacted in a state in 1975.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1970-2016	0.000	0.000	0.000	0.3936	1.000	1.000
2000-2016	0.000	0.000	1.000	0.6453	1.000	1.000

5. renewport – Did state adopt State Renewable Portfolio Standards? (dichotomous variable: 0 or 1) First enacted in 1991.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1970-2016	0.000	0.000	0.000	0.165	0.000	1.000
2000-2016	0.000	0.000	0.000	0.3782	1.000	1.000

6. bldstds_yearadopted – Did state adopt Environmental Building Standards? (dichotomous variable: 0 or 1). First enacted 1991.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1970-2016	0.000	0.000	0.000	0.2041	0.000	1.000
2000-2016	0.000	0.000	1.000	0.527	1.000	1.000

7. corporaterenew_yearadopted – Did state adopt Tax Credits For Renewable Technologies? (dichotomous variable: 0 or 1). First enacted 1990.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1970-2016	0.000	0.000	0.000	0.05558	0.000	1.000
2000-2016	0.000	0.000	0.000	0.1297	0.000	1.000

8. ewaste – Did state adopt State E-Waste Disposal Programs? (dichotomous variable: 0 or 1). First enacted 2003.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1970-2016	0.000	0.000	0.000	0.1003	0.000	1.000
2000-2016	0.000	0.000	0.000	0.2773	1.000	1.000

9. netmeter_yearadopted – Did state adopt Implement Onsite Renewable Energy Generation? (dichotomous variable: 0 or 1). First enacted in 1990.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1970-2016	0.000	0.000	0.000	0.2844	1.000	1.000
2000-2016	0.000	0.000	1.000	0.6951	1.000	1.000

10. personaltax_yearadopted – Did state adopt Residential Tax Credits For Renewable Energy Systems? (dichotomous variable: 0 or 1). First enacted 1990.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1970-2016	0.000	0.000	0.000	0.135	0.000	1.000
2000-2016	0.000	0.000	0.000	0.3145	1.000	1.000

11. personaltaxeff_yearadopted – Did state adopt Residential Tax Credits For Efficiency? (dichotomous variable: 0 or 1) First enacted 1990.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1970-2016	0.000	0.000	0.000	0.07599	0.000	1.000
2000-2016	0.000	0.000	0.000	0.1861	0.000	1.000

- Energy index summary stats:

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1970-2016	-4.9588	-4.9588	-2.8261	-0.1087	2.2816	27.2889
2000-2016	-4.959	-0.622	4.901	6.006	11.489	27.289

Using definitions from the Correlates of State Policy dataset, the Air Quality Index five policies are and with descriptive statistics (non-standardized) created from R (Correlates of State Policy):

1. environment_ca_car_emissions_sta – Does the state adopt California's Car emissions standards (which are more stringent than the federal level)? (dichotomous variable: 0 or 1). First enacted in 2003.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1970-2016	0.000	0.000	0.000	0.07642	0.000	1.000
2000-2016	0.000	0.000	0.000	0.2113	0.000	1.000

2. environment_state_nepas – Does the state have its version of the federal National Environmental Policy Act? (dichotomous variable: 0 or 1). First enacted in 1970.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1970-2016	0.000	0.000	0.000	0.2788	1.000	1.000
2000-2016	0.000	0.000	0.000	0.3061	1.000	1.000

3. environment_ghg_cap – Does the state have a binding cap on greenhouse gas emissions in the utility sector? (dichotomous variable: 0 or 1) First enacted in 2006.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1970-2016	0.000	0.000	0.000	0.04863	0.000	1.000
2000-2016	0.000	0.000	0.000	0.1345	0.000	1.000

4. fcap – 'Active cap on greenhouse gas emissions from electric power producers? (1=yes, 0=no) (note: setting a goal or initiating a process doesn't count - only actual regulations in force) First enacted in 2008.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1970-2016	0.000	0.000	0.000	0.03908	0.000	1.000
2000-2016	0.000	0.000	0.000	0.108	0.000	1.000

5. fgastax1 – Gasoline tax rate per gallon in dollars, including sales, excise, storage, and franchise taxes. (Continuous variable). First enacted in 2000.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1970-2016	0.000	0.000	0.000	0.08462	0.1900	0.5280
2000-2016	0.000	0.180	0.220	0.234	0.280	0.528

- Air index summary stats:

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1970-2016	-1.900	-1.900	-0.6271	-0.0493	0.3422	14.0353
2000-2016	-1.5818	-0.3089	0.4866	2.1749	2.9595	14.0353

Also, due to three reasons the study analyzed the data by breaking up the time periods from 1970-2016 and from 2000-2016. First, due to there being a change in policies first being enacted in 2000 when before states were barely enacting any pro-environmental policies.

	Policies Enacted	Total Policies Analyzed in Indices
1975	3	16
1990	7	16
2000	12	16

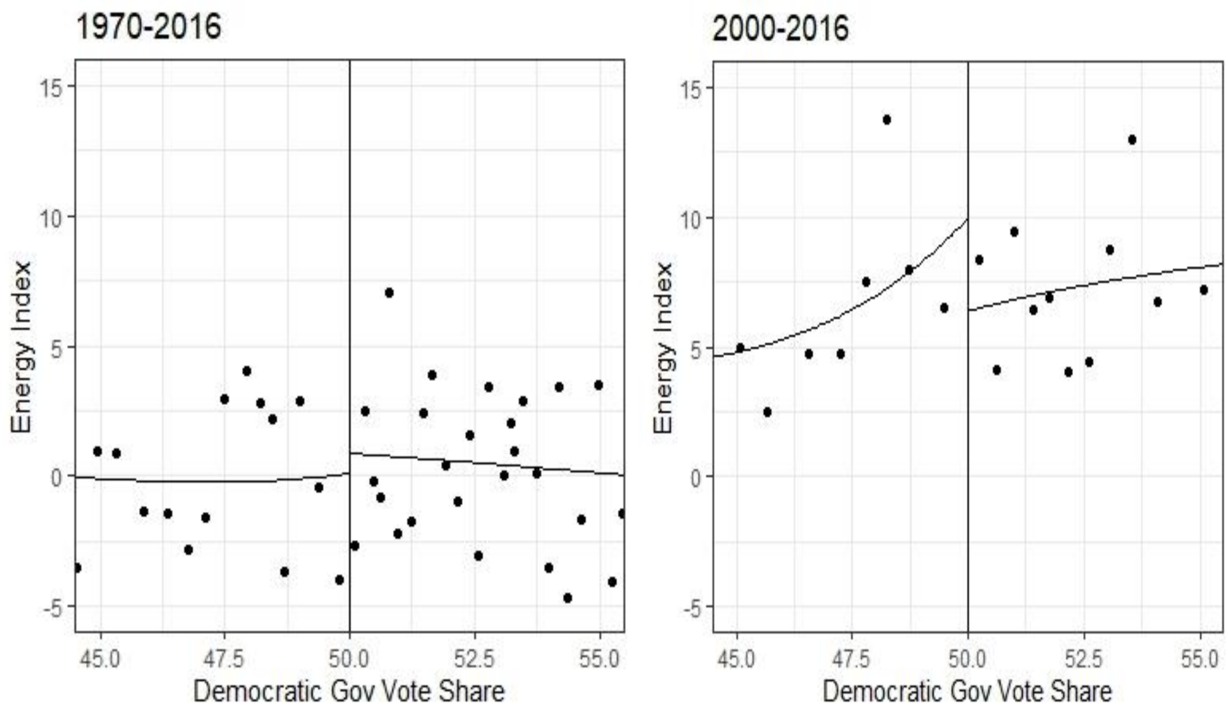
Second, due to Gallup polling suggesting the environment became a more partisan issue around 2000 when it was likely bipartisan before then (Gallup; 2020). Since the first poll was first conducted in 2000 and only most recently since 2005, another poll is used since 1992 which demonstrates that caring about the environment has become a more salient issue for the population only more recently and has increased in salience over time.

	Democratic Party	Republican Party
Trust given party to protect the quality of the nation's environment a great deal or moderate amount (2000):	56%	43%
Trust given party to protect the quality of the nation's environment a great deal or moderate amount (2005):	52%	41%

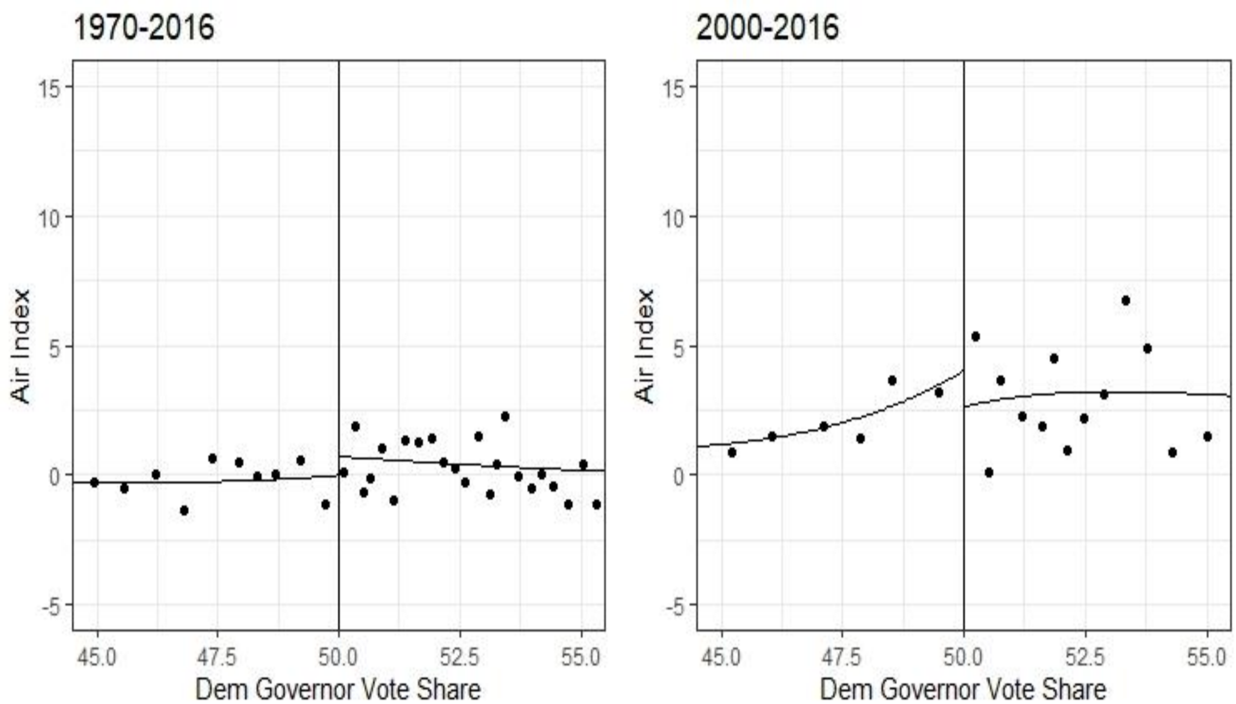
	Very Well	Fairly well	Not Very Well	Not at All	No Opinion
How well do you understand climate change (1992)?	11%	42%	22%	22%	3%
How well do you understand climate change (2001)?	15%	54%	22%	6%	1%
How well do you understand climate change (2016)?	24%	55%	16%	5%	0%

Finally, this division of analysis between 1970-2016 and 2000-2016 aligns with findings from Caughey that suggested around 2000 partisan ideology sorted with Democrats being liberals and Republicans being conservative which was not particularly the case before 2000 (Caughey, et. al; 2017).

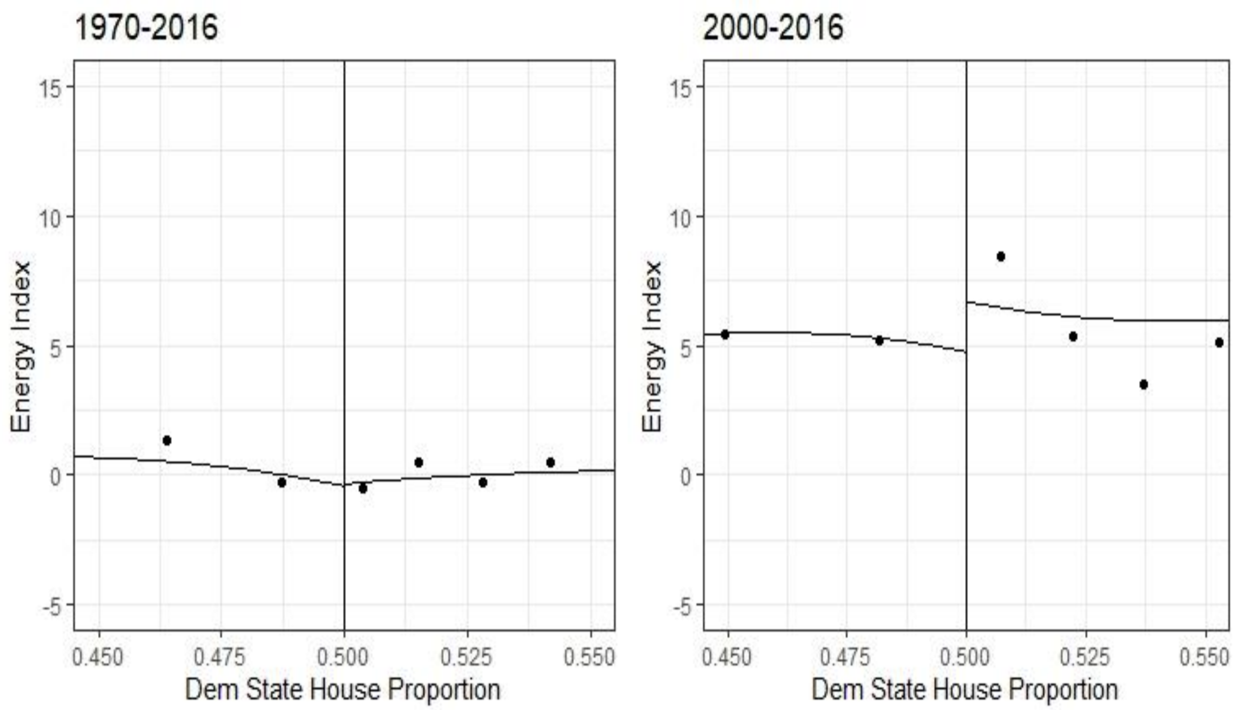
V. Results and Discussion



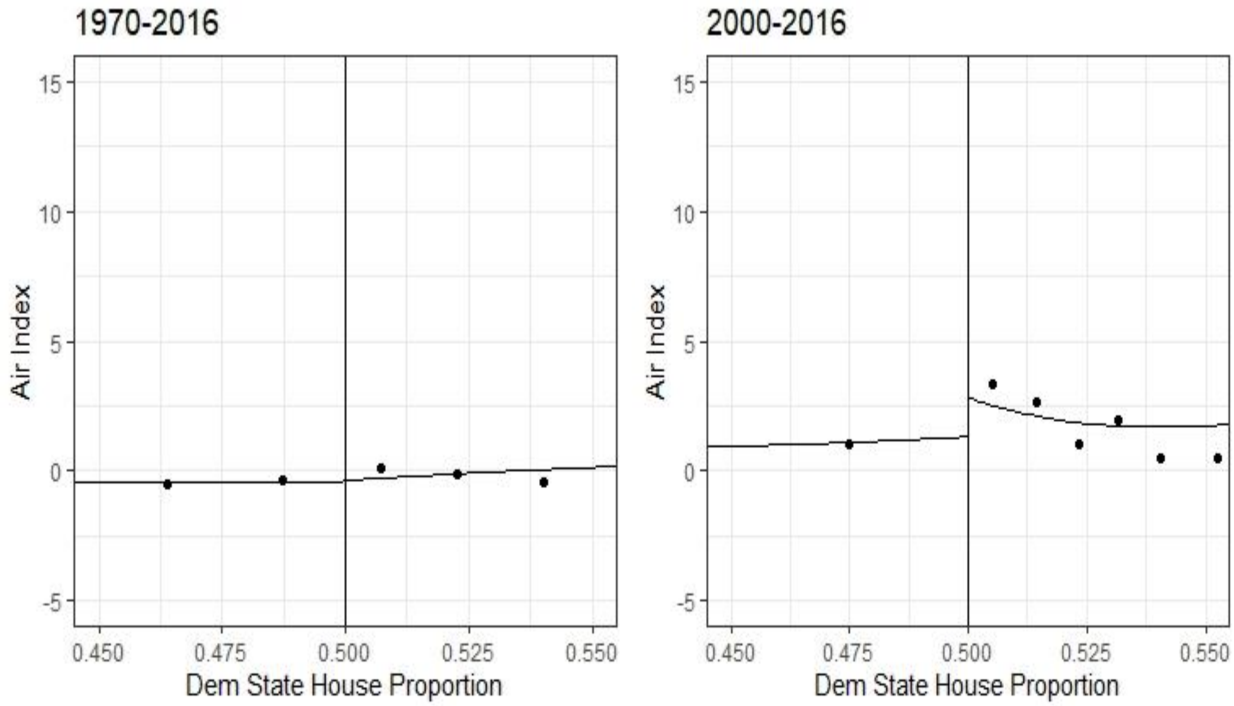
First, looking at the regression discontinuity plot, which takes bins of the data and creates point estimates to better visualize and estimate the data around the cutoff of 50% of the Democratic share of the vote for governor, it shows mixed conclusions. Between 1970-2016 it appears that Democratic governors led to a slight increase in pro-environmental energy policy, but that trend appears to have reversed itself since 2000 and Republican governors now appear to create more pro-environmental energy policy. However, using a significance level of 0.05 only the 1970-2016 change is significant with a p-value < 0.001, while the 2000-2016 change is not significant with a p-value = 0.066. (See appendix for summary of RD plot and RD Robust).



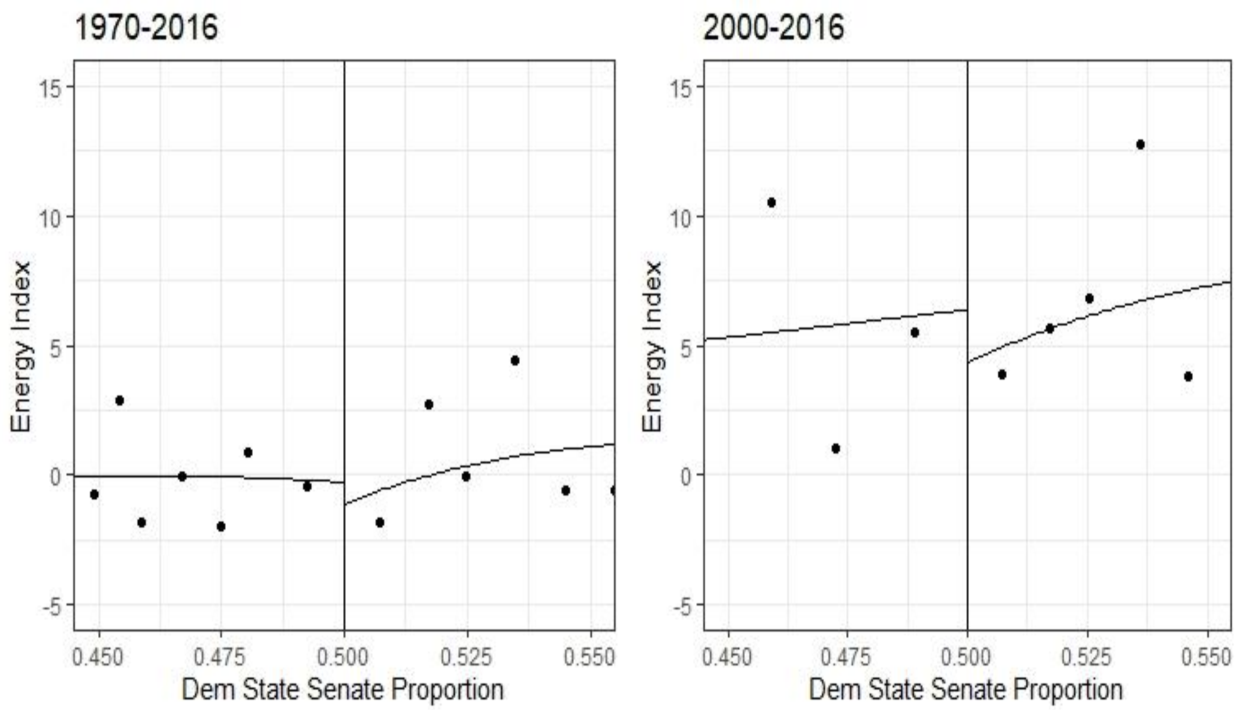
Next, looking at the RD plots created from R for the governor air index suggests mixed evidence. From 1970-2016, it appears that Democratic governors do create more pro-environmental policy with a cutoff set at 50% of the vote which is significant at the 0.05 level with a p-value < 0.001. However, from 2000-2016 it appears that Democratic governors do not create more pro-environmental policy, however this difference is not significant at the 0.05 level with a p-value = 0.178. (See appendix for summary of RD plot and RD Robust).



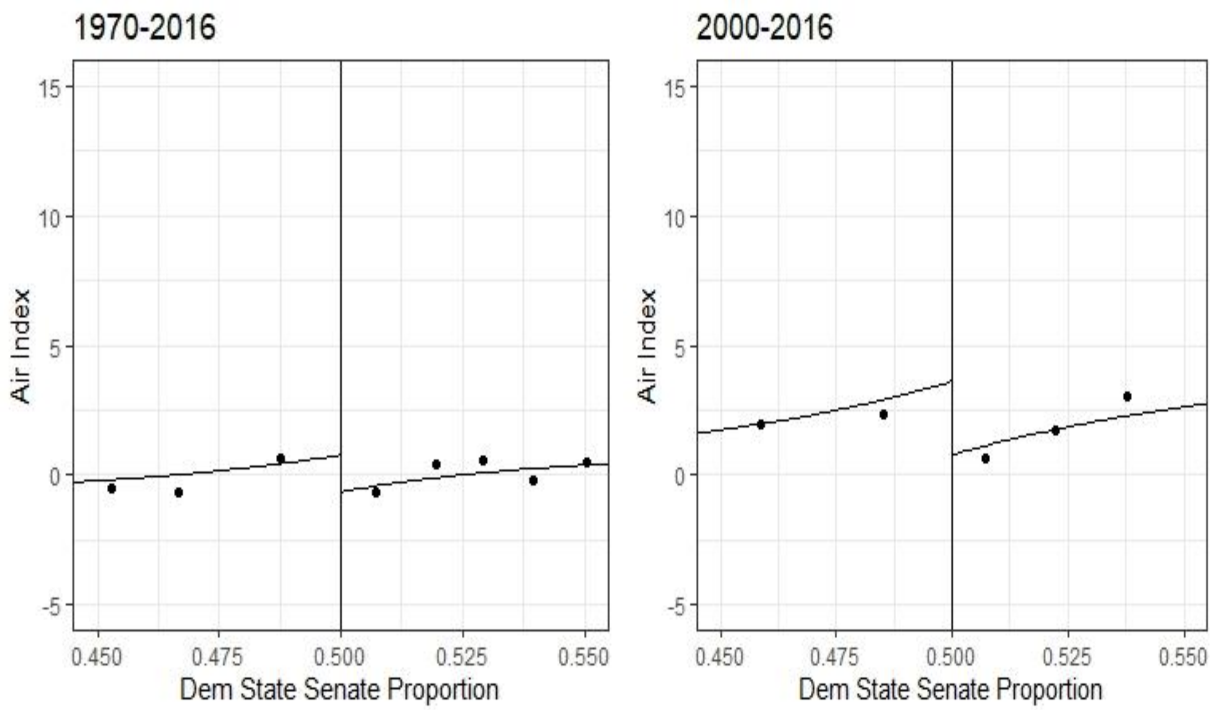
Next, looking at the RD plot created from R for the house energy index suggests mixed results. Between 1970-2016 there is essentially no difference between a Democratic House or a Republican House in terms of energy policy. However, between 2000-2016 the data suggests that Democrats in the House do create more pro-environmental energy policy, but this increase is not significant at the 0.05 level with a p-value = 0.438. (See appendix for summary of RD plot and RD Robust).



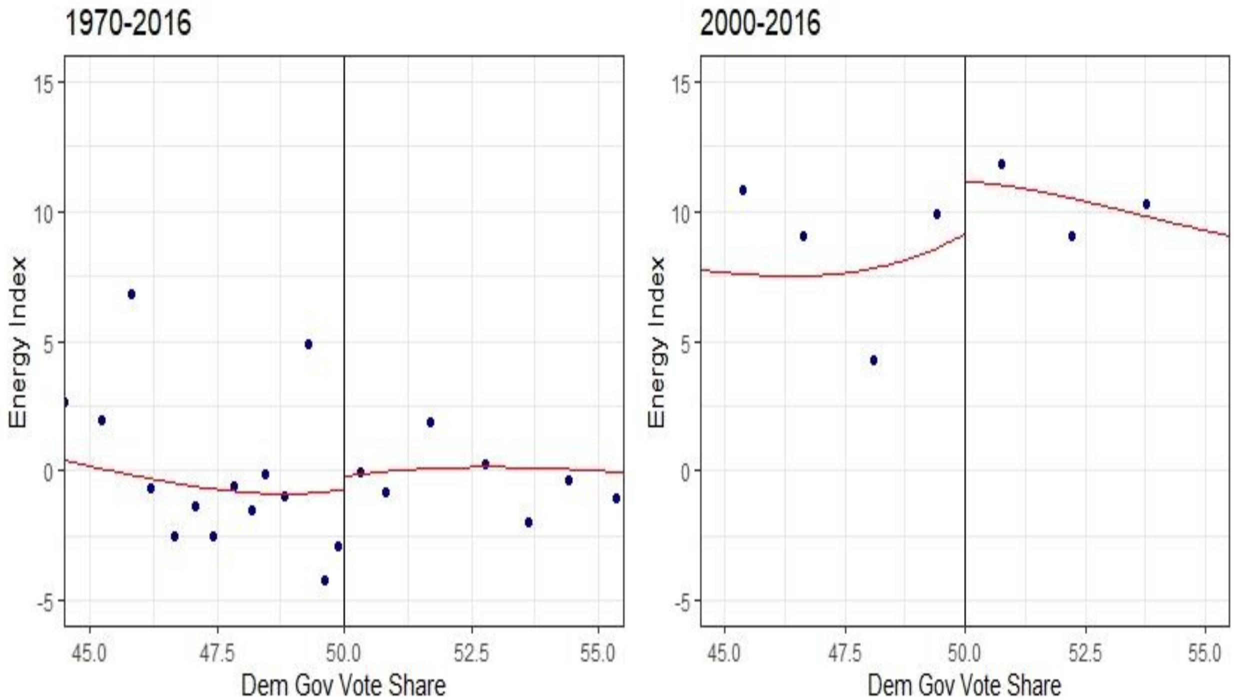
Next, looking at the RD plot created from R for the house air index there is more consistent results. Between 1970-2016 there is a small increase with a Democratic House in terms of air policy, but this increase is not significant at the 0.05 level with a p-value = 0.231. However, between 2000-2016 the data suggests that Democrats in the House do create more pro-environmental air policy and this increase is significant at the 0.05 level with a p-value < 0.001. (See appendix for summary of RD plot and RD Robust).



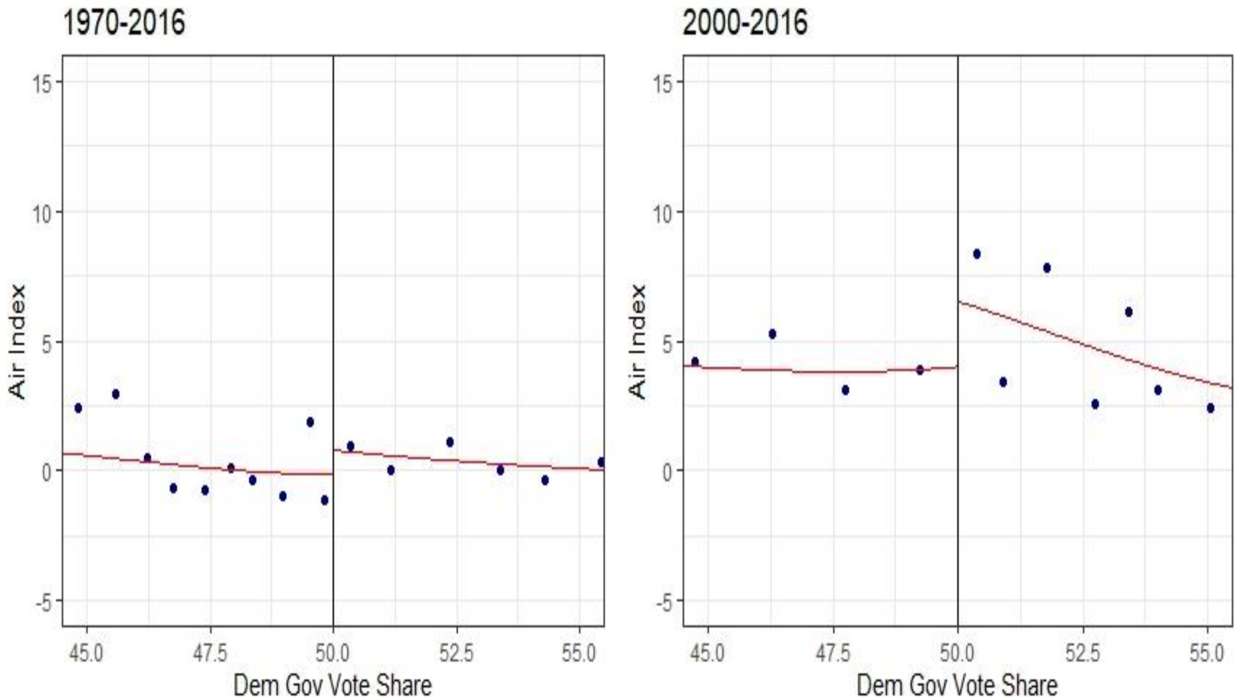
Next, looking at the RD plot created from R for the senate energy index suggest that a Democratic senate creates less pro-environmental policy than the Republican senate for both the 1970-2016 years and 2000-2016 years. However, both of these are not significant at the 0.05 level with p-values = 0.955 and 0.662 respectively. (See appendix for summary of RD plot and RD Robust).



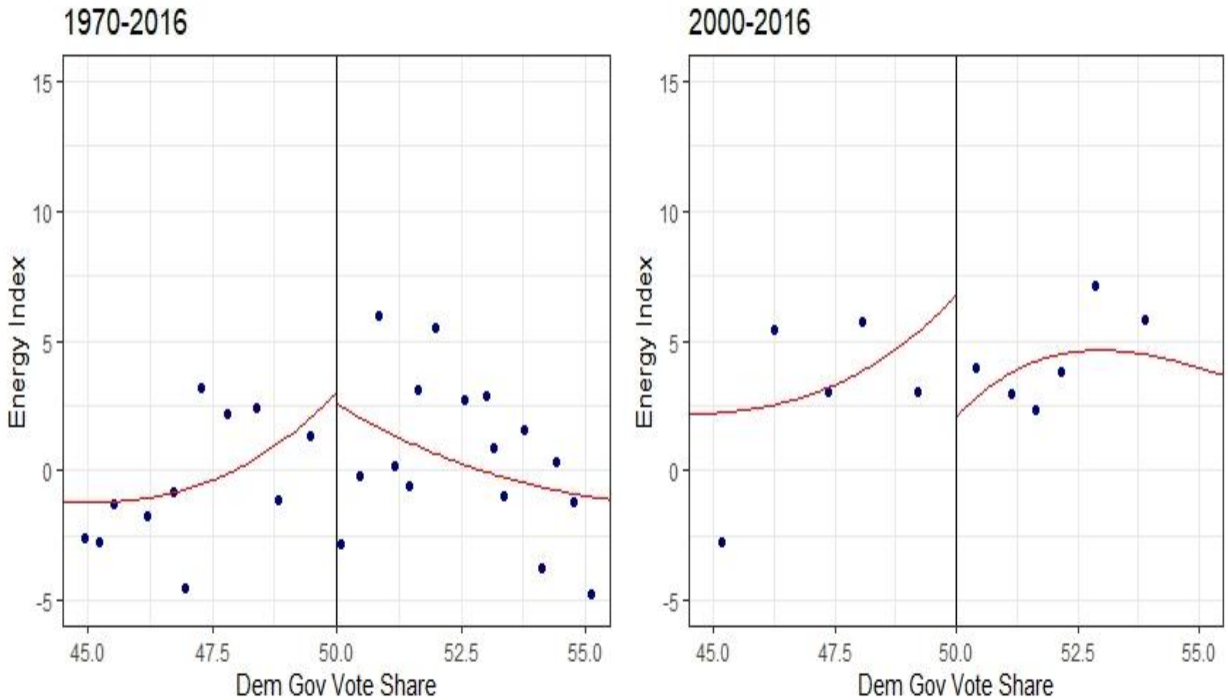
Next, looking at the RD plot created from R for the senate air index suggests consistent results that a Democratic senate creates less pro-environmental policy than the Republican senate for both the 1970-2016 years and 2000-2016 years. However, only the 2000-2016 years are significant at the 0.05 level with p-values = 0.001 while the 1970-2016 years only have a p-value =0.054. (See appendix for summary of RD plot and RD Robust).



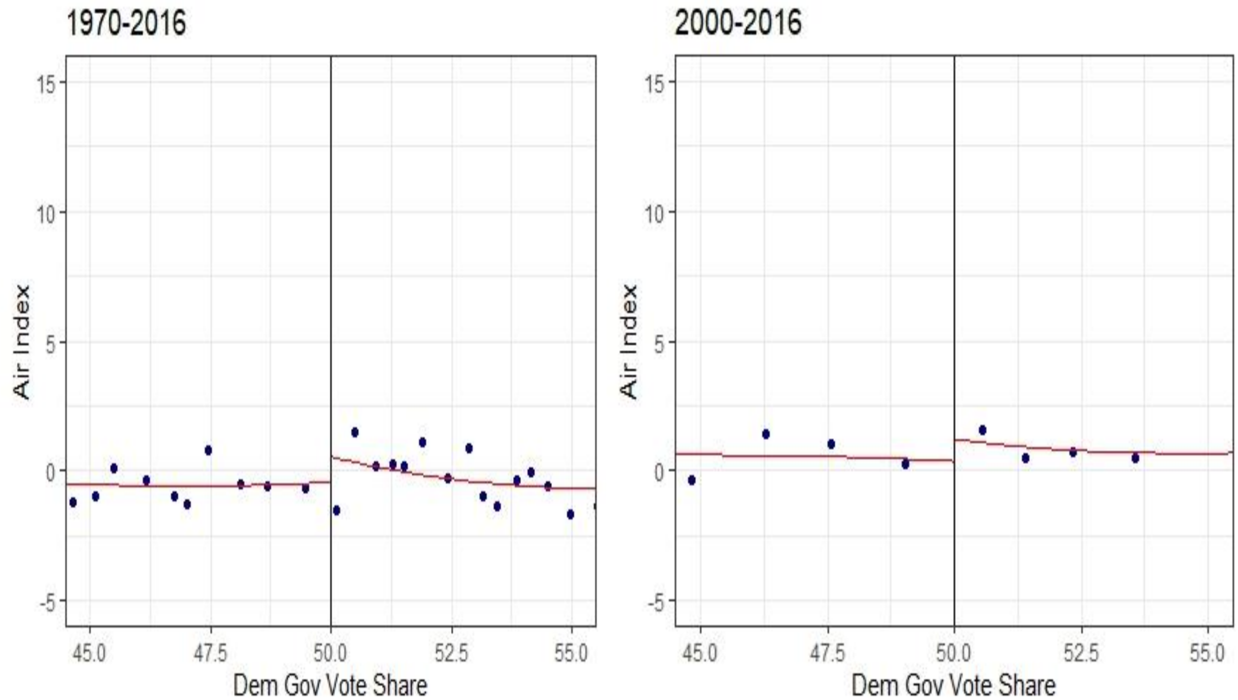
Next, the data attempts to capture the difference between unified and divided government. So, a subset of the data is taken that only looks at unified democratic state legislatures and then observes what happens at the margins if a Democratic or Republican governor is added. On the energy index for both the 1970 and 2000 timelines electing a Democratic governor with a unified Democratic legislature leads to a significant increase in the energy index with a p-value of less than 0.05 with 0.027 and 0.046 respectively.



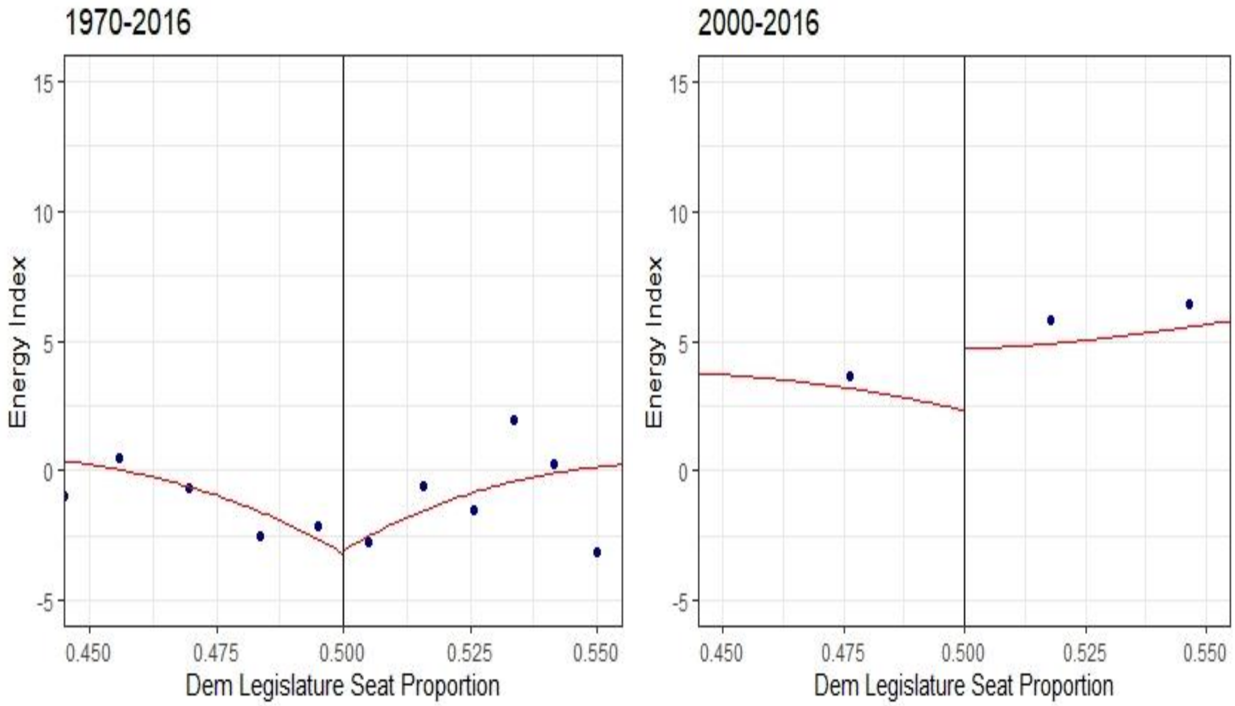
Similarly, on the air index for both the 1970 and 2000 timelines electing a Democratic governor with a unified Democratic legislature leads to a significant increase in the air index with a p-value of less than 0.05 with 0.002 and 0.011 respectively.



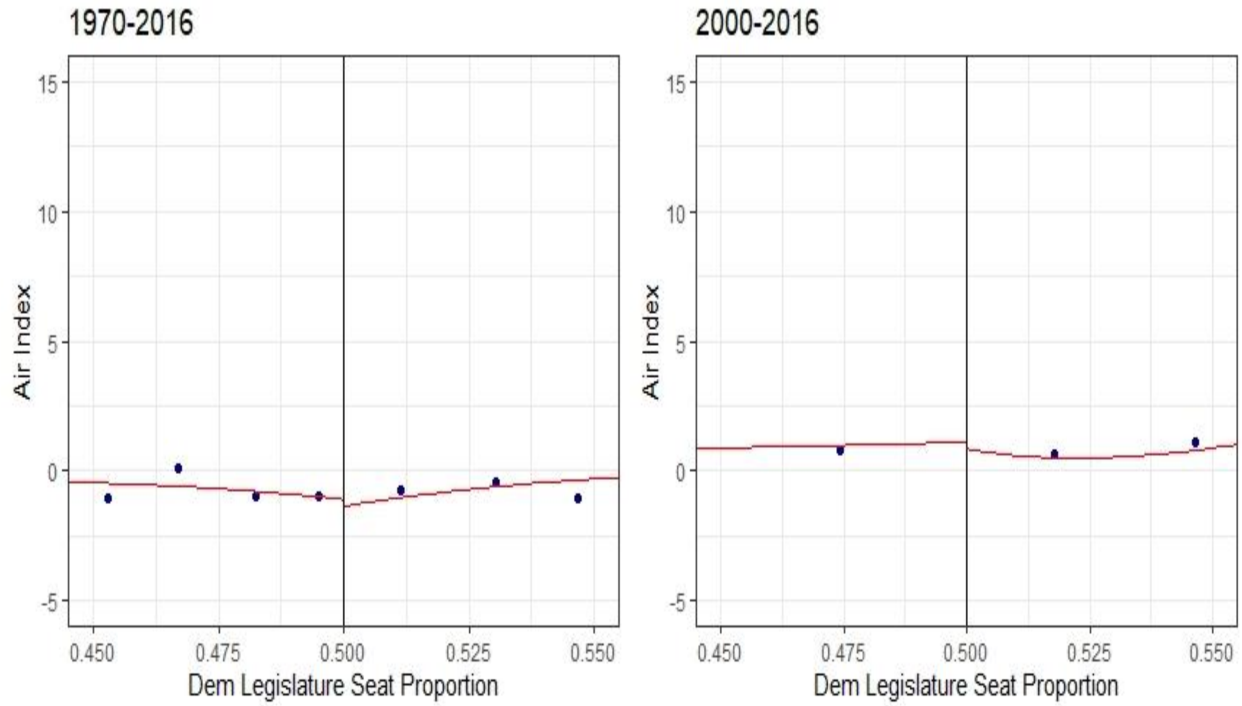
Next, taking a subset of state legislatures that are not unified and Democratic, adding a Democratic governor with a non-unified and Democratic state legislature decreases the energy index for both the 1970 and 2000 timelines. To be clear, this subset includes unified Republican legislatures, divided Republican legislatures, and divided Democratic legislatures, but not unified Democratic state legislatures. However, note that this is not significant at the 0.05 level with a p-value of 0.814 and 0.331 respectively.



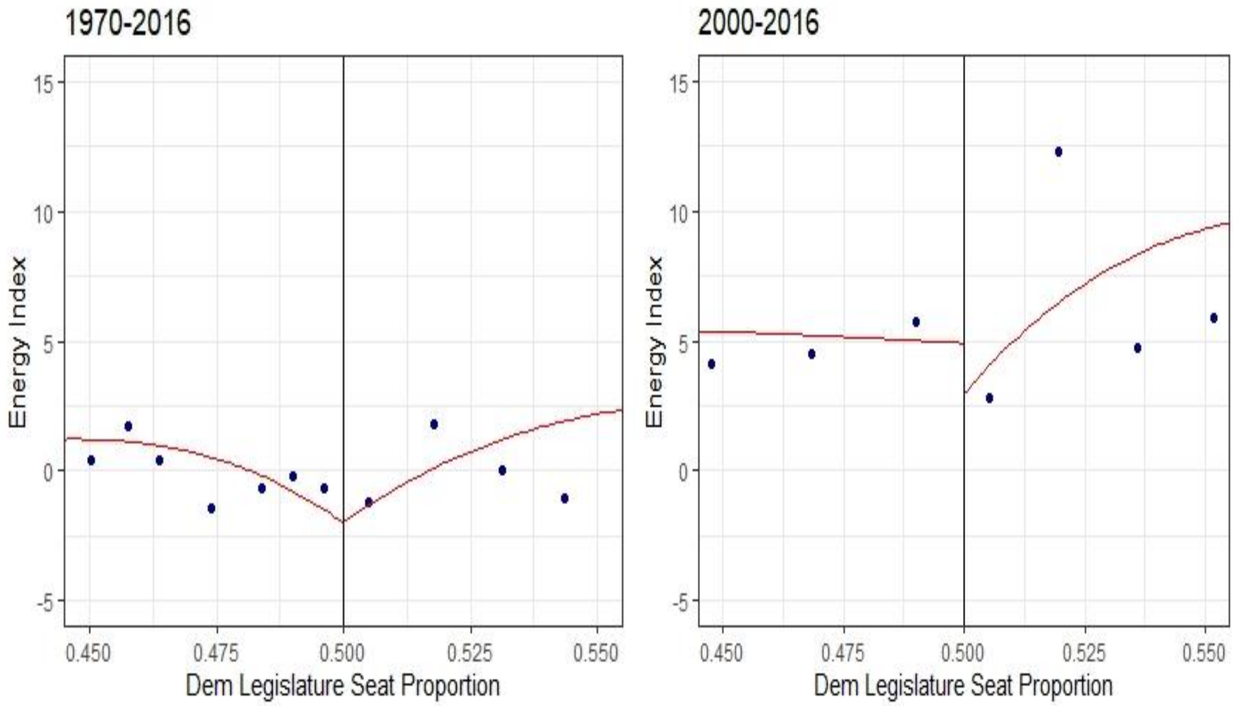
Similarly, looking at the air index for the subset without unified Democratic state legislatures it shows that electing a Democratic governor significantly increases the air index on both the 1970 and 2000 timelines. This increase was significant at the level of 0.05 with a p-value of 0.006 and 0.005 respectively.



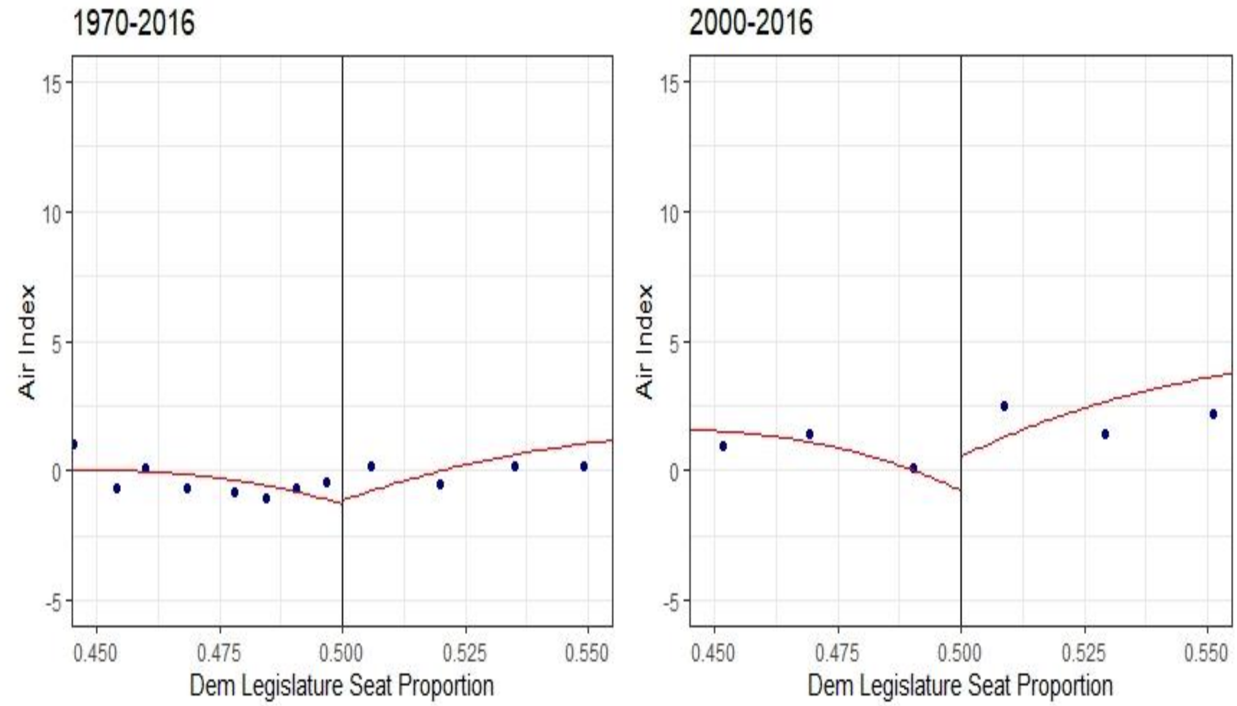
In contrast, a subset now is taken with a Republican governor and control of the state legislature is converted into one variable with the total proportion of Democratic state legislature seats in both chambers averaged to form one proportion. Here a proportion above 0.5 indicates a Democratic state legislature and a proportion below 0.5 indicates a Republican state legislature. Adding a Democratic state legislature to a Republican governor both in the 1970 and 2000 timelines leads to an increase in the Energy Index however note that neither of these are significant at the 0.05 level with a p-value of 0.454 and 0.358 respectively.



However, on the air index adding a Democratic state legislature to a Republican governor both in the 1970 and 2000 timelines leads to an increase and a decrease respectively in the Air Index however note that neither of these are significant at the 0.05 level with a p-value of 0.408 and 0.732 respectively.



Now if a subset is taken of only Democratic governors and adding a Democratic state legislature to that shows an increase and a decrease respectively on the 1970 and 2000 timelines on the Energy Index. Note that neither of these are significant at the 0.05 level with a p-value of 0.973 a nd 0.714 respectively.



Finally, on the air index adding a Democratic state legislature to a Democratic governor leads to a significant increase on both the 1970 and 2000 timelines. However, only the 2000 timeline is significant at the 0.05 level with p-values of 0.069 and 0.001 respectively.

1970 – 2016: RD Robust vs. Years of Governor

	Coefficient	Standard Error	P-value
First Year - Energy	1.288	1.545	0.405
Second Year – Energy	0.961	1.537	0.532
Third Year - Energy	0.804	1.533	0.600
Fourth Year – Energy	0.703	1.567	0.654
First Year – Air	0.548	0.686	0.424
Second Year – Air	0.780	0.672	0.246
Third Year – Air	0.620	0.643	0.336
Fourth Year - Air	0.681	0.701	0.332

2000 – 2016: RD Robust vs. Years of Governor

	Coefficient	Standard Error	P-value
First Year - Energy	-3.201	3.135	0.307
Second Year – Energy	-2.672	2.811	0.342
Third Year - Energy	-2.232	3.123	0.475
Fourth Year – Energy	-2.732	3.178	0.390
First Year – Air	-1.378	1.677	0.411
Second Year – Air	-0.406	1.512	0.788
Third Year – Air	-0.278	1.320	0.833
Fourth Year - Air	-0.197	1.5777	0.900

Next, looking at the differences in years in office for governors appears to have mixed evidence. Between 1970-2016 it appears that Democratic governors do lead to more pro-environmental policy, but between 2000-2016 we see that instead it is Republican governors that lead to more pro-environmental policy. However, none of these coefficients are significant at the 0.05 level. One trend that is clear though is it appears that governors affect policy less the longer they are in office which is consistent with the findings from Kousser and Phillips which suggested that the longer a governor is in office, the less effective he is at making policy (Kousser and Phillips; 2012).

Below, the study performed regression analysis for each area of government in relation to the Air Quality Index or the Energy Index. Note: that Dem. Dummy, Dem. Senate, and Dem. House are dichotomous variables with 0 being a Republican or Republican majority holds control of the position or 1 being a Democrat or Democratic majority holds control of the position.

Air Gov

1970-2016

```
          Estimate Std. Error t value Pr(>|t|)
Dem.Dummy 0.076447   0.221124  0.3457   0.7296
Gov.Year  0.019119   0.029449  0.6492   0.5163
```

2000-2016

```
           Estimate Std. Error t value Pr(>|t|)
Dem.Dummy  0.972085   0.371408  2.6173 0.009034 **
Gov.Year  -0.045944   0.022743 -2.0201 0.043712 *
```

Energy Gov

1970-2016

```
            Estimate Std. Error t value Pr(>|t|)
Dem.Dummy -0.7392530  0.5774123 -1.2803   0.2006
Gov.Year  -0.0073964  0.0661476 -0.1118   0.9110
```

2000-2016

```
           Estimate Std. Error t value Pr(>|t|)
Dem.Dummy  0.640229   0.669538  0.9562 0.339254
Gov.Year  -0.152284   0.047841 -3.1831 0.001515 **
```

Energy Sen

1970-2016

```
        Estimate Std. Error t value Pr(>|t|)
Dem.Sen -2.29455    0.96318 -2.3823  0.01729 *
```

2000-2016

```
        Estimate Std. Error t value Pr(>|t|)
Dem.Sen -0.60759    1.03290 -0.5882   0.5565
```

Air Sen

1970-2016

```
        Estimate Std. Error t value Pr(>|t|)
Dem.Sen -0.22528    0.33781 -0.6669   0.5049
```

2000-2016

```
        Estimate Std. Error t value Pr(>|t|)
Dem.Sen  0.33111    0.32801  1.0095   0.3131
```

Energy House

1970-2016

```
          Estimate Std. Error t value Pr(>|t|)
Dem.House -2.92701    0.91793 -3.1887 0.001449 **
```

2000-2016

```
          Estimate Std. Error t value Pr(>|t|)
Dem.House -1.04276    0.98752 -1.0559   0.2913
```

Air House

1970-2016

```
          Estimate Std. Error t value Pr(>|t|)
Dem.House -0.10230    0.37873 -0.2701   0.7871
```

2000-2016

```
          Estimate Std. Error t value Pr(>|t|)
Dem.House  0.90491    0.53225  1.7001   0.0895 .
```

So, looking at the regression results that consider the entire data set rather than just on the margins when elections are close, it shows above that some major takeaways stand out. The analysis changes drastically when looking at 2000-2016 vs. looking at 1970-2016. One being that it appears more current Democrats have passed more pro-environmental policy than Democrats in the past. Also, both Democrats in the House and Senate appear to pass more pro-environmental air policy, however this change is not significant at the 0.05 level. While, Republicans appear to pass more pro-environmental energy policy, however this change is also not significant at the 0.05 level. At the gubernatorial level though, it appears that Democratic governors pass more pro-environmental energy and air policy with air policy being significant at the 0.05 level with a p-value = 0.009. Also, as shown in the RD robust analysis that a governor's ability to pass both pro-environmental air and energy policy decreases the longer that he/she is office which is consistent with Kousser and Phillips's findings.

Energy Unified Government

```
                       Estimate Std. Error t value Pr(>|t|)
Unified.Dem.Government -0.303730   1.362435 -0.2229 0.823647
Gov.Year               -0.149797   0.049891 -3.0025 0.002763 **
```

Air Unified Government

```
                    Estimate Std. Error t value Pr(>|t|)
Unified.Government  1.621670   0.661858  2.4502  0.01450 *
Gov.Year           -0.053893   0.022048 -2.4444  0.01473 *
```

In this section, divided vs. unified government is explored. So a new variable is created so if each chamber is Democratic then the variable equals one, but if each chamber is Republican then the variable equals zero. To further account for divided government each chamber that is held by Democrats is given 0.33. For this an assumption is made that all three chambers are equal at creating/passing policy. So for example if there is a Democratic governor and a Democratic state senate then it would receive a score of 0.67. Here the data shows that on the energy index electing Republicans leads to slightly more pro-environmental energy policy all though this change is not significant, but electing Democrats leads to significantly more pro-environmental air policy.

VI. Future Research Proposals

So where should future studies seek to go given these results? Next, would be examining the effectiveness of these environmental policies targeted in the air and energy indexes at lowering emissions and then if the lowering of these emissions has increased life expectancy for Americans. There is some literature already in these areas. One study looks at the adverse effects of major pollutants that many of these environmental policies seek to limit (Majewsky and Jääskeläinen; 2019). It finds that nitrogen oxides produced in high temperature fuel combustion create smog, acid rain, and nitrate particulates, while destroying stratospheric ozone, and lowering human health. Particulates from combustion of wood and fossil fuels that reduce atmospheric visibility, lower human health, and create black carbon particulates that contribute to global warming. Sulfur dioxide from coal combustion and diesel engines that produce acid rain and lower human health. Ozone created from photochemical smog that produce damage to crops, plants, and man-made products and lower human health. Carbon monoxide created from combustion of motor vehicles that lower human health. Carbon dioxide created from fossil fuel and wood combustion that produces the most common greenhouse gas. Non-methane hydrocarbons created from combustion and solvent utilization that produces photochemical smog. Methane created natural gas combustion and produces greenhouse gas. Chlorofluorocarbons created from solvents, aerosol, and refrigerants that destroy stratospheric ozone (Majewsky and Jääskeläinen; 2019). In this way, by lowering these emissions would suggest that human life expectancy and quality of life would increase.

VII. Conclusion

Voters often vote with the mindset that the representatives they elect will fulfill the policies they advocate for. However, the data suggest party control in environmental policy does matter, just not in the same way voters think it does. Pro-environmental policy in the states appears to be a bipartisan issue with Democrats passing significantly more pro-environmental air policies and some weak evidence suggesting Republicans passing more pro-environmental energy policies. Whether looking at the governorship, the results differ though with Democrats passing more pro-environmental air and energy policies, but especially more environmental air policies. Also, governor's ability to pass these policies appears to decrease the longer they are in office which is consistent with the findings from Kousser and Phillips. Looking at unified vs. divided government shows party and policies become difficult to pass during divided government, but particularly in unified Democratic government pro-environmental policies, both energy and air, pass at significantly higher rates. So overall, perhaps instead that environmental policy is more of a bipartisan issue. The data show that both parties are concerned about the issue but are just attacking the issue in different ways. That both parties recognize can improve the quality of life and the life expectancy of Americans, but it may just be thought to be legislated by different ways among the two parties.

VIII. Appendix

A. Governor Energy Index

1970-2016

Number of Obs.	2303	
Kernel	Uniform	

Number of Obs.	1076	1227
Eff. Number of Obs.	1076	1227
Order poly. fit (p)	4	4
BW poly. fit (h)	29.750	39.190
Number of bins scale	1	1
Bins Selected	30	58
Average Bin Length	0.990	0.676
Median Bin Length	0.492	0.316
IMSE-optimal bins	30	58
Mimicking Variance bins	135	124
Relative to IMSE-optimal:		
Implied scale	1.000	1.000
WIMSE variance weight	0.500	0.500
WIMSE bias weight	0.500	0.500

Number of Obs.	2303
BW type	mserd
Kernel	Triangular
VCE method	NN

Number of Obs.	1076	1227
Eff. Number of Obs.	428	452
Order est. (p)	1	1
Order bias (q)	2	2
BW est. (h)	4.419	4.419
BW bias (b)	9.779	9.779
rho (h/b)	0.452	0.452
Unique Obs.	277	307

Method	Coef.	Std. Err.	z	P>|z|	[95% C.I.]
Conventional	1.781	0.447	3.985	0.000	[0.905 , 2.657]
Robust	-	-	4.154	0.000	[1.070 , 2.981]

2000-2016

Number of Obs.	832	
Kernel	Uniform	

Number of Obs.	445	387
Eff. Number of Obs.	445	387
Order poly. fit (p)	4	4
BW poly. fit (h)	29.750	25.590
Number of bins scale	1	1

```
Bins Selected                     21             21
Average Bin Length             1.412          1.223
Median Bin Length              0.900          0.640

IMSE-optimal bins                 21             21
Mimicking Variance bins           55             66

Relative to IMSE-optimal:
Implied scale                  1.000          1.000
WIMSE variance weight          0.500          0.500
WIMSE bias weight              0.500          0.500

Number of Obs.                   832
BW type                        mserd
Kernel                    Triangular
VCE method                        NN

Number of Obs.                   445         387
Eff. Number of Obs.              162         195
Order est. (p)                     1           1
Order bias  (q)                    2           2
BW est. (h)                    5.020       5.020
BW bias (b)                    9.239       9.239
rho (h/b)                      0.543       0.543
Unique Obs.                      130         115

=============================================================================
        Method     Coef. Std. Err.         z     P>|z|      [ 95% C.I. ]
=============================================================================
  Conventional    -1.490     0.811    -1.836     0.066    [-3.080 , 0.100]
        Robust         -         -    -1.217     0.224    [-2.959 , 0.692]
=============================================================================
```

B. Governor Air Index

```
1970-2016

Number of Obs.                  2303
Kernel                       Uniform

Number of Obs.                  1076           1227
Eff. Number of Obs.             1076           1227
Order poly. fit (p)                4              4
BW poly. fit (h)              29.750         39.190
Number of bins scale               1              1

Bins Selected                     21             52
Average Bin Length             1.415          0.754
Median Bin Length              0.684          0.352

IMSE-optimal bins                 21             52
Mimicking Variance bins          120            122

Relative to IMSE-optimal:
Implied scale                  1.000          1.000
WIMSE variance weight          0.500          0.500
WIMSE bias weight              0.500          0.500
```

Number of Obs.	2303	
BW type	mserd	
Kernel	Triangular	
VCE method	NN	

Number of Obs.	1076	1227
Eff. Number of Obs.	605	610
Order est. (p)	1	1
Order bias (q)	2	2
BW est. (h)	6.709	6.709
BW bias (b)	10.046	10.046
rho (h/b)	0.668	0.668
Unique Obs.	277	307

Method	Coef.	Std. Err.	z	P>|z|	[95% C.I.]
Conventional	0.782	0.187	4.171	0.000	[0.415 , 1.149]
Robust	-	-	3.878	0.000	[0.408 , 1.242]

2000-2016

Number of Obs.	832	
Kernel	Uniform	

Number of Obs.	445	387
Eff. Number of Obs.	445	387
Order poly. fit (p)	4	4
BW poly. fit (h)	29.750	25.590
Number of bins scale	1	1
Bins Selected	16	25
Average Bin Length	1.853	1.028
Median Bin Length	1.095	0.532
IMSE-optimal bins	16	25
Mimicking Variance bins	50	62
Relative to IMSE-optimal:		
Implied scale	1.000	1.000
WIMSE variance weight	0.500	0.500
WIMSE bias weight	0.500	0.500

Number of Obs.	832	
BW type	mserd	
Kernel	Triangular	
VCE method	NN	

Number of Obs.	445	387
Eff. Number of Obs.	188	211
Order est. (p)	1	1
Order bias (q)	2	2
BW est. (h)	6.016	6.016
BW bias (b)	8.942	8.942
rho (h/b)	0.673	0.673
Unique Obs.	130	115

Method	Coef.	Std. Err.	z	P>|z|	[95% C.I.]
Conventional	-0.526	0.391	-1.346	0.178	[-1.291 , 0.240]
Robust	-	-	-1.013	0.311	[-1.329 , 0.423]

C. House Energy Index

1970-2016

Number of Obs.	2303	
Kernel	Uniform	
Number of Obs.	884	1419
Eff. Number of Obs.	884	1419
Order poly. fit (p)	4	4
BW poly. fit (h)	0.371	0.500
Number of bins scale	1	1
Bins Selected	10	24
Average Bin Length	0.037	0.021
Median Bin Length	0.023	0.016
IMSE-optimal bins	10	24
Mimicking Variance bins	71	81
Relative to IMSE-optimal:		
Implied scale	1.000	1.000
WIMSE variance weight	0.500	0.500
WIMSE bias weight	0.500	0.500

Number of Obs.	2303	
BW type	mserd	
Kernel	Triangular	
VCE method	NN	
Number of Obs.	884	1419
Eff. Number of Obs.	476	633
Order est. (p)	1	1
Order bias (q)	2	2
BW est. (h)	0.124	0.124
BW bias (b)	0.211	0.211
rho (h/b)	0.588	0.588
Unique Obs.	260	369

Method	Coef.	Std. Err.	z	P>|z|	[95% C.I.]
Conventional	-0.095	0.788	-0.121	0.904	[-1.639 , 1.449]
Robust	-	-	0.166	0.868	[-1.651 , 1.956]

2000-2016

Number of Obs.	833	
Kernel	Uniform	
Number of Obs.	428	405
Eff. Number of Obs.	428	405
Order poly. fit (p)	4	4
BW poly. fit (h)	0.371	0.420
Number of bins scale	1	1
Bins Selected	9	15
Average Bin Length	0.041	0.028
Median Bin Length	0.031	0.019

```
IMSE-optimal bins               9             15
Mimicking Variance bins        34             39

Relative to IMSE-optimal:
Implied scale               1.000          1.000
WIMSE variance weight       0.500          0.500
WIMSE bias weight           0.500          0.500

Number of Obs.                833
BW type                     mserd
Kernel                 Triangular
VCE method                     NN

Number of Obs.                428         405
Eff. Number of Obs.           132         139
Order est. (p)                  1           1
Order bias  (q)                 2           2
BW est. (h)                 0.086       0.086
BW bias (b)                 0.140       0.140
rho (h/b)                   0.609       0.609
Unique Obs.                   163         141

==============================================================================
        Method     Coef. Std. Err.         z     P>|z|      [ 95% C.I. ]
==============================================================================
  Conventional     1.625     2.097     0.775     0.438    [-2.485 , 5.735]
        Robust         -         -     0.834     0.404    [-2.783 , 6.903]
==============================================================================
```

D. House Air Index

```
1970-2016

Number of Obs.               2303
Kernel                    Uniform

Number of Obs.                884           1419
Eff. Number of Obs.           884           1419
Order poly. fit (p)             4              4
BW poly. fit (h)            0.371          0.500
Number of bins scale            1              1

Bins Selected                  10             17
Average Bin Length          0.037          0.030
Median Bin Length           0.023          0.020

IMSE-optimal bins              10             17
Mimicking Variance bins        62             75

Relative to IMSE-optimal:
Implied scale               1.000          1.000
WIMSE variance weight       0.500          0.500
WIMSE bias weight           0.500          0.500
```

Number of Obs.	2303
BW type	mserd
Kernel	Triangular
VCE method	NN

Number of Obs.	884	1419
Eff. Number of Obs.	378	474
Order est. (p)	1	1
Order bias (q)	2	2
BW est. (h)	0.098	0.098
BW bias (b)	0.182	0.182
rho (h/b)	0.536	0.536
Unique Obs.	260	369

Method	Coef.	Std. Err.	z	P>|z|	[95% C.I.]
Conventional	0.343	0.287	1.197	0.231	[-0.219 , 0.905]
Robust	-	-	1.400	0.162	[-0.180 , 1.080]

2000-2016

Number of Obs.	833
Kernel	Uniform

Number of Obs.	428	405
Eff. Number of Obs.	428	405
Order poly. fit (p)	4	4
BW poly. fit (h)	0.371	0.420
Number of bins scale	1	1
Bins Selected	6	24
Average Bin Length	0.061	0.018
Median Bin Length	0.043	0.013
IMSE-optimal bins	6	24
Mimicking Variance bins	25	33
Relative to IMSE-optimal:		
Implied scale	1.000	1.000
WIMSE variance weight	0.500	0.500
WIMSE bias weight	0.500	0.500

Number of Obs.	833
BW type	mserd
Kernel	Triangular
VCE method	NN

Number of Obs.	428	405
Eff. Number of Obs.	83	99
Order est. (p)	1	1
Order bias (q)	2	2
BW est. (h)	0.057	0.057
BW bias (b)	0.107	0.107
rho (h/b)	0.536	0.536
Unique Obs.	163	141

```
================================================================================
        Method     Coef. Std. Err.         z     P>|z|      [ 95% C.I. ]
================================================================================
  Conventional     2.200     0.630     3.490     0.000     [0.964 , 3.435]
        Robust         -         -     3.499     0.000     [1.073 , 3.805]
================================================================================
```

E. Senate Energy Index

```
1970-2016

Number of Obs.                2303
Kernel                     Uniform

Number of Obs.                 942            1361
Eff. Number of Obs.            942            1361
Order poly. fit (p)              4               4
BW poly. fit (h)             0.414           0.500
Number of bins scale             1               1

Bins Selected                   31              31
Average Bin Length           0.013           0.016
Median Bin Length            0.009           0.014

IMSE-optimal bins               31              31
Mimicking Variance bins         89              96

Relative to IMSE-optimal:
Implied scale                1.000           1.000
WIMSE variance weight        0.500           0.500
WIMSE bias weight            0.500           0.500


Number of Obs.                2303
BW type                      mserd
Kernel                  Triangular
VCE method                      NN

Number of Obs.                 942        1361
Eff. Number of Obs.            367         409
Order est. (p)                   1           1
Order bias  (q)                  2           2
BW est. (h)                  0.090       0.090
BW bias (b)                  0.151       0.151
rho (h/b)                    0.598       0.598
Unique Obs.                    139         224

================================================================================
        Method     Coef. Std. Err.         z     P>|z|      [ 95% C.I. ]
================================================================================
  Conventional    -0.073     1.300    -0.056     0.955    [-2.622 , 2.476]
        Robust         -         -     0.014     0.989    [-3.216 , 3.261]
================================================================================
```

2000-2016

Number of Obs.	833	
Kernel	Uniform	
Number of Obs.	441	392
Eff. Number of Obs.	441	392
Order poly. fit (p)	4	4
BW poly. fit (h)	0.414	0.460
Number of bins scale	1	1
Bins Selected	22	24
Average Bin Length	0.018	0.019
Median Bin Length	0.013	0.014
IMSE-optimal bins	22	24
Mimicking Variance bins	37	43
Relative to IMSE-optimal:		
Implied scale	1.000	1.000
WIMSE variance weight	0.500	0.500
WIMSE bias weight	0.500	0.500

Number of Obs.	833	
BW type	mserd	
Kernel	Triangular	
VCE method	NN	
Number of Obs.	441	392
Eff. Number of Obs.	232	232
Order est. (p)	1	1
Order bias (q)	2	2
BW est. (h)	0.138	0.138
BW bias (b)	0.212	0.212
rho (h/b)	0.651	0.651
Unique Obs.	104	95

Method	Coef.	Std. Err.	z	P>|z|	[95% C.I.]
Conventional	-0.741	1.693	-0.438	0.662	[-4.058 , 2.577]
Robust	-	-	-0.331	0.741	[-4.850 , 3.450]

F. Senate Air Index

1970-2016

Number of Obs.	2303	
Kernel	Uniform	
Number of Obs.	942	1361
Eff. Number of Obs.	942	1361
Order poly. fit (p)	4	4
BW poly. fit (h)	0.414	0.500
Number of bins scale	1	1

Bins Selected	13	29
Average Bin Length	0.031	0.017
Median Bin Length	0.018	0.018
IMSE-optimal bins	13	29
Mimicking Variance bins	80	80
Relative to IMSE-optimal:		
Implied scale	1.000	1.000
WIMSE variance weight	0.500	0.500
WIMSE bias weight	0.500	0.500

Number of Obs.	2303
BW type	mserd
Kernel	Triangular
VCE method	NN

Number of Obs.	942	1361
Eff. Number of Obs.	369	414
Order est. (p)	1	1
Order bias (q)	2	2
BW est. (h)	0.094	0.094
BW bias (b)	0.179	0.179
rho (h/b)	0.524	0.524
Unique Obs.	139	224

Method	Coef.	Std. Err.	z	P>|z|	[95% C.I.]
Conventional	-1.103	0.574	-1.923	0.054	[-2.228 , 0.021]
Robust	-	-	-1.904	0.057	[-2.625 , 0.038]

2000-2016

Number of Obs.	833
Kernel	Uniform

Number of Obs.	441	392
Eff. Number of Obs.	441	392
Order poly. fit (p)	4	4
BW poly. fit (h)	0.414	0.460
Number of bins scale	1	1
Bins Selected	12	13
Average Bin Length	0.034	0.036
Median Bin Length	0.024	0.025
IMSE-optimal bins	12	13
Mimicking Variance bins	41	37
Relative to IMSE-optimal:		
Implied scale	1.000	1.000
WIMSE variance weight	0.500	0.500
WIMSE bias weight	0.500	0.500

Number of Obs.	833
BW type	mserd
Kernel	Triangular
VCE method	NN

Number of Obs.	441	392
Eff. Number of Obs.	91	109
Order est. (p)	1	1
Order bias (q)	2	2
BW est. (h)	0.070	0.070
BW bias (b)	0.138	0.138
rho (h/b)	0.509	0.509
Unique Obs.	104	95

Method	Coef.	Std. Err.	z	P>|z|	[95% C.I.]
Conventional	-3.715	1.129	-3.291	0.001	[-5.928 , -1.502]
Robust	-	-	-3.151	0.002	[-6.676 , -1.556]

G. Unified Dem State Legislature with Dem Governor on Energy Index

1970-2016

Number of Obs.	1132
Kernel	Uniform

Number of Obs.	477	655
Eff. Number of Obs.	477	655
Order poly. fit (p)	4	4
BW poly. fit (h)	28.610	34.900
Number of bins scale	1	1
Bins Selected	26	18
Average Bin Length	1.099	1.941
Median Bin Length	0.507	1.160
IMSE-optimal bins	26	18
Mimicking Variance bins	46	50
Relative to IMSE-optimal:		
Implied scale	1.000	1.000
WIMSE variance weight	0.500	0.500
WIMSE bias weight	0.500	0.500

Number of Obs.	1132
BW type	mserd
Kernel	Triangular
VCE method	NN

Number of Obs.	477	655
Eff. Number of Obs.	257	262
Order est. (p)	1	1
Order bias (q)	2	2
BW est. (h)	6.016	6.016
BW bias (b)	10.198	10.198
rho (h/b)	0.590	0.590
Unique Obs.	141	188

Method	Coef.	Std. Err.	z	P>|z|	[95% C.I.]

Method	Coef.	Std. Err.	z	P>|z|	[95% C.I.]
Conventional	1.857	0.837	2.217	0.027	[0.215 , 3.498]
Robust	-	-	2.366	0.018	[0.376 , 4.012]

2000-2016

Number of Obs.	313
Kernel	Uniform

Number of Obs.	168	145
Eff. Number of Obs.	168	145
Order poly. fit (p)	4	4
BW poly. fit (h)	28.610	24.130
Number of bins scale	1	1
Bins Selected	10	8
Average Bin Length	2.851	3.029
Median Bin Length	1.428	1.690
IMSE-optimal bins	10	8
Mimicking Variance bins	16	14
Relative to IMSE-optimal:		
Implied scale	1.000	1.000
WIMSE variance weight	0.500	0.500
WIMSE bias weight	0.500	0.500

Number of Obs.	313
BW type	mserd
Kernel	Triangular
VCE method	NN

Number of Obs.	168	145
Eff. Number of Obs.	71	61
Order est. (p)	1	1
Order bias (q)	2	2
BW est. (h)	5.232	5.232
BW bias (b)	8.694	8.694
rho (h/b)	0.602	0.602
Unique Obs.	53	48

Method	Coef.	Std. Err.	z	P>|z|	[95% C.I.]
Conventional	5.024	2.523	1.992	0.046	[0.080 , 9.968]
Robust	-	-	2.099	0.036	[0.396 , 11.598]

H. Unified Dem State Legislature with Dem Governor on Air Index

1970-2016

Number of Obs.	1132
Kernel	Uniform

Number of Obs.	477	655
Eff. Number of Obs.	477	655
Order poly. fit (p)	4	4
BW poly. fit (h)	28.610	34.900
Number of bins scale	1	1

```
Bins Selected                    19             15
Average Bin Length            1.504          2.329
Median Bin Length             0.740          1.278

IMSE-optimal bins                19             15
Mimicking Variance bins          51             46

Relative to IMSE-optimal:
Implied scale                 1.000          1.000
WIMSE variance weight         0.500          0.500
WIMSE bias weight             0.500          0.500

Number of Obs.                  1132
BW type                        mserd
Kernel                    Triangular
VCE method                        NN

Number of Obs.                  477         655
Eff. Number of Obs.             257         258
Order est. (p)                    1           1
Order bias  (q)                   2           2
BW est. (h)                   5.870       5.870
BW bias (b)                  10.925      10.925
rho (h/b)                     0.537       0.537
Unique Obs.                     141         188

=============================================================================
        Method     Coef. Std. Err.         z     P>|z|      [ 95% C.I. ]
=============================================================================
  Conventional     1.262     0.417     3.026     0.002     [0.444 , 2.079]
        Robust         -         -     3.118     0.002     [0.535 , 2.346]
=============================================================================


2000-2016

Number of Obs.                  168            145
Eff. Number of Obs.             168            145
Order poly. fit (p)               4              4
BW poly. fit (h)             28.610         24.130
Number of bins scale              1              1

Bins Selected                     9             16
Average Bin Length            3.168          1.514
Median Bin Length             1.497          0.970

IMSE-optimal bins                 9             16
Mimicking Variance bins          17             16

Relative to IMSE-optimal:
Implied scale                 1.000          1.000
WIMSE variance weight         0.500          0.500
WIMSE bias weight             0.500          0.500

Number of Obs.                   313
BW type                        mserd
Kernel                    Triangular
VCE method                        NN

Number of Obs.                  168         145
Eff. Number of Obs.              74          61
Order est. (p)                    1           1
Order bias  (q)                   2           2
BW est. (h)                   5.565       5.565
```

BW bias (b)	8.067	8.067
rho (h/b)	0.690	0.690
Unique Obs.	53	48

Method	Coef.	Std. Err.	z	P>|z|	[95% C.I.]
Conventional	3.275	1.289	2.540	0.011	[0.748 , 5.801]
Robust	-	-	2.273	0.023	[0.476 , 6.438]

I. Non-Unified Dem State Legislature with Dem Governor on Energy Index

1970-2016

Number of Obs.	378	327
Eff. Number of Obs.	378	327
Order poly. fit (p)	4	4
BW poly. fit (h)	29.750	39.190
Number of bins scale	1	1
Bins Selected	30	28
Average Bin Length	0.965	1.428
Median Bin Length	0.545	0.545
IMSE-optimal bins	30	28
Mimicking Variance bins	36	31
Relative to IMSE-optimal:		
Implied scale	1.000	1.000
WIMSE variance weight	0.500	0.500
WIMSE bias weight	0.500	0.500

Number of Obs.	705
BW type	mserd
Kernel	Triangular
VCE method	NN

Number of Obs.	378	327
Eff. Number of Obs.	142	188
Order est. (p)	1	1
Order bias (q)	2	2
BW est. (h)	5.441	5.441
BW bias (b)	10.969	10.969
rho (h/b)	0.496	0.496
Unique Obs.	117	112

Method	Coef.	Std. Err.	z	P>|z|	[95% C.I.]
Conventional	-0.304	1.291	-0.236	0.814	[-2.835 , 2.227]
Robust	-	-	-0.562	0.574	[-3.783 , 2.097]

2000-2016

Number of Obs.	363
Kernel	Uniform

Number of Obs.	199	164
Eff. Number of Obs.	199	164
Order poly. fit (p)	4	4

BW poly. fit (h)	29.750	23.090
Number of bins scale	1	1
Bins Selected	16	10
Average Bin Length	1.797	2.409
Median Bin Length	1.137	1.615
IMSE-optimal bins	16	10
Mimicking Variance bins	20	16
Relative to IMSE-optimal:		
Implied scale	1.000	1.000
WIMSE variance weight	0.500	0.500
WIMSE bias weight	0.500	0.500

Number of Obs.	363
BW type	mserd
Kernel	Triangular
VCE method	NN

Number of Obs.	199	164
Eff. Number of Obs.	46	97
Order est. (p)	1	1
Order bias (q)	2	2
BW est. (h)	4.381	4.381
BW bias (b)	8.424	8.424
rho (h/b)	0.520	0.520
Unique Obs.	68	57

Method	Coef.	Std. Err.	z	P>|z|	[95% C.I.]
Conventional	-2.128	2.189	-0.972	0.331	[-6.419 , 2.163]
Robust	-	-	-1.145	0.252	[-8.074 , 2.120]

J. Non-Unified Dem State Legislature with Dem Governor on Air Index

1970-2000

Number of Obs.	705
Kernel	Uniform

Number of Obs.	378	327
Eff. Number of Obs.	378	327
Order poly. fit (p)	4	4
BW poly. fit (h)	29.750	39.190
Number of bins scale	1	1
Bins Selected	26	25
Average Bin Length	1.113	1.600
Median Bin Length	0.710	0.545
IMSE-optimal bins	26	25
Mimicking Variance bins	26	28
Relative to IMSE-optimal:		
Implied scale	1.000	1.000

```
WIMSE variance weight        0.500          0.500
WIMSE bias weight            0.500          0.500

Number of Obs.                 705
BW type                      mserd
Kernel                  Triangular
VCE method                      NN

Number of Obs.                378        327
Eff. Number of Obs.           143        192
Order est. (p)                  1          1
Order bias  (q)                 2          2
BW est. (h)                 5.658      5.658
BW bias (b)                10.162     10.162
rho (h/b)                   0.557      0.557
Unique Obs.                   117        112

=============================================================================
        Method     Coef. Std. Err.         z     P>|z|      [ 95% C.I. ]
=============================================================================
  Conventional     0.950     0.347     2.737     0.006     [0.270 , 1.631]
        Robust         -         -     2.460     0.014     [0.209 , 1.850]
=============================================================================


2000-2016



Number of Obs.                 363
Kernel                     Uniform

Number of Obs.                199            164
Eff. Number of Obs.           199            164
Order poly. fit (p)             4              4
BW poly. fit (h)           29.750         23.090
Number of bins scale            1              1

Bins Selected                  12              7
Average Bin Length          2.396          3.441
Median Bin Length           1.445          2.070

IMSE-optimal bins              12              7
Mimicking Variance bins        14             13

Relative to IMSE-optimal:
Implied scale               1.000          1.000
WIMSE variance weight       0.500          0.500
WIMSE bias weight           0.500          0.500

Number of Obs.                 363
BW type                      mserd
Kernel                  Triangular
VCE method                      NN

Number of Obs.                199        164
Eff. Number of Obs.            51         97
Order est. (p)                  1          1
Order bias  (q)                 2          2
BW est. (h)                 4.541      4.541
BW bias (b)                 9.746      9.746
rho (h/b)                   0.466      0.466
Unique Obs.                    68         57
```

Method	Coef.	Std. Err.	z	P>|z|	[95% C.I.]
Conventional	1.741	0.624	2.790	0.005	[0.518 , 2.965]
Robust	-	-	2.741	0.006	[0.564 , 3.391]

K.Dem Governor with Dem Seat Proportion on Energy Index

1970-2016

Number of Obs.	1079
Kernel	Uniform

Number of Obs.	539	540
Eff. Number of Obs.	539	540
Order poly. fit (p)	4	4
BW poly. fit (h)	0.393	0.476
Number of bins scale	1	1
Bins Selected	20	29
Average Bin Length	0.020	0.016
Median Bin Length	0.012	0.010
IMSE-optimal bins	20	29
Mimicking Variance bins	34	33
Relative to IMSE-optimal:		
Implied scale	1.000	1.000
WIMSE variance weight	0.500	0.500
WIMSE bias weight	0.500	0.500

Number of Obs.	1079
BW type	mserd
Kernel	Triangular
VCE method	NN

Number of Obs.	539	540
Eff. Number of Obs.	178	189
Order est. (p)	1	1
Order bias (q)	2	2
BW est. (h)	0.081	0.081
BW bias (b)	0.130	0.130
rho (h/b)	0.621	0.621
Unique Obs.	274	301

Method	Coef.	Std. Err.	z	P>|z|	[95% C.I.]
Conventional	0.603	0.805	0.748	0.454	[-0.976 , 2.181]
Robust	-	-	0.505	0.614	[-1.369 , 2.319]

2000-2016

Number of Obs.	449
Kernel	Uniform

Number of Obs.	292	157
Eff. Number of Obs.	292	157
Order poly. fit (p)	4	4

BW poly. fit (h)	0.393	0.406
Number of bins scale	1	1
Bins Selected	9	11
Average Bin Length	0.043	0.037
Median Bin Length	0.031	0.027
IMSE-optimal bins	9	11
Mimicking Variance bins	18	17
Relative to IMSE-optimal:		
Implied scale	1.000	1.000
WIMSE variance weight	0.500	0.500
WIMSE bias weight	0.500	0.500

Number of Obs.	449
BW type	mserd
Kernel	Triangular
VCE method	NN

Number of Obs.	292	157
Eff. Number of Obs.	72	55
Order est. (p)	1	1
Order bias (q)	2	2
BW est. (h)	0.082	0.082
BW bias (b)	0.135	0.135
rho (h/b)	0.607	0.607
Unique Obs.	167	92

Method	Coef.	Std. Err.	z	P>|z|	[95% C.I.]
Conventional	2.343	2.547	0.920	0.358	[-2.649 , 7.335]
Robust	-	-	0.695	0.487	[-3.971 , 8.335]

L.Dem Governor with Dem Seat Proportion on Air Index

1970-2016

Number of Obs.	1079
Kernel	Uniform

Number of Obs.	539	540
Eff. Number of Obs.	539	540
Order poly. fit (p)	4	4
BW poly. fit (h)	0.393	0.476
Number of bins scale	1	1
Bins Selected	19	14
Average Bin Length	0.021	0.034
Median Bin Length	0.015	0.022
IMSE-optimal bins	19	14
Mimicking Variance bins	32	30
Relative to IMSE-optimal:		
Implied scale	1.000	1.000
WIMSE variance weight	0.500	0.500

```
WIMSE bias weight            0.500          0.500

Number of Obs.                1079
BW type                      mserd
Kernel                  Triangular
VCE method                      NN

Number of Obs.                539         540
Eff. Number of Obs.           159         157
Order est. (p)                  1           1
Order bias  (q)                 2           2
BW est. (h)                 0.072       0.072
BW bias (b)                 0.131       0.131
rho (h/b)                   0.550       0.550
Unique Obs.                   274         301
```

```
=============================================================================
        Method     Coef. Std. Err.         z     P>|z|      [ 95% C.I. ]
=============================================================================
  Conventional     0.204     0.247     0.827     0.408    [-0.279 , 0.688]
        Robust         -         -     1.100     0.272    [-0.242 , 0.862]
=============================================================================
```

2000-2016

```
Number of Obs.                 449
Kernel                     Uniform

Number of Obs.                292            157
Eff. Number of Obs.           292            157
Order poly. fit (p)             4              4
BW poly. fit (h)            0.393          0.406
Number of bins scale            1              1

Bins Selected                   8             11
Average Bin Length          0.048          0.037
Median Bin Length           0.041          0.027

IMSE-optimal bins               8             11
Mimicking Variance bins        17             18

Relative to IMSE-optimal:
Implied scale               1.000          1.000
WIMSE variance weight       0.500          0.500
WIMSE bias weight           0.500          0.500

Number of Obs.                 449
BW type                      mserd
Kernel                  Triangular
VCE method                      NN

Number of Obs.                292         157
Eff. Number of Obs.            52          41
Order est. (p)                  1           1
Order bias  (q)                 2           2
BW est. (h)                 0.070       0.070
BW bias (b)                 0.128       0.128
rho (h/b)                   0.546       0.546
Unique Obs.                   167          92
```

Method	Coef.	Std. Err.	z	P>|z|	[95% C.I.]
Conventional	-0.294	0.857	-0.342	0.732	[-1.974 , 1.387]
Robust	-	-	0.011	0.991	[-1.955 , 1.976]

M. Republican Governor with Dem Seat Proportion on Energy Index

1970-2016

Number of Obs.	1224	
Kernel	Uniform	
Number of Obs.	370	854
Eff. Number of Obs.	370	854
Order poly. fit (p)	4	4
BW poly. fit (h)	0.350	0.500
Number of bins scale	1	1
Bins Selected	22	20
Average Bin Length	0.016	0.025
Median Bin Length	0.010	0.023
IMSE-optimal bins	22	20
Mimicking Variance bins	39	42
Relative to IMSE-optimal:		
Implied scale	1.000	1.000
WIMSE variance weight	0.500	0.500
WIMSE bias weight	0.500	0.500

Number of Obs.	1224	
BW type	mserd	
Kernel	Triangular	
VCE method	NN	
Number of Obs.	370	854
Eff. Number of Obs.	158	246
Order est. (p)	1	1
Order bias (q)	2	2
BW est. (h)	0.078	0.078
BW bias (b)	0.117	0.117
rho (h/b)	0.663	0.663
Unique Obs.	206	425

Method	Coef.	Std. Err.	z	P>|z|	[95% C.I.]
Conventional	0.036	1.057	0.034	0.973	[-2.036 , 2.109]
Robust	-	-	0.002	0.998	[-2.492 , 2.496]

2000-2016

Number of Obs.	384	
Kernel	Uniform	
Number of Obs.	149	235
Eff. Number of Obs.	149	235
Order poly. fit (p)	4	4
BW poly. fit (h)	0.350	0.411

Number of bins scale	1	1
Bins Selected	8	14
Average Bin Length	0.043	0.030
Median Bin Length	0.023	0.018
IMSE-optimal bins	8	14
Mimicking Variance bins	16	22
Relative to IMSE-optimal:		
Implied scale	1.000	1.000
WIMSE variance weight	0.500	0.500
WIMSE bias weight	0.500	0.500

Number of Obs.	384
BW type	mserd
Kernel	Triangular
VCE method	NN

Number of Obs.	149	235
Eff. Number of Obs.	59	76
Order est. (p)	1	1
Order bias (q)	2	2
BW est. (h)	0.065	0.065
BW bias (b)	0.104	0.104
rho (h/b)	0.629	0.629
Unique Obs.	97	132

Method	Coef.	Std. Err.	z	P>|z|	[95% C.I.]
Conventional	-0.661	1.801	-0.367	0.714	[-4.191 , 2.869]
Robust	-	-	-0.545	0.586	[-5.300 , 2.995]

N. Republican Governor with Dem Seat Proportion on Air Index

1970-2016

Number of Obs.	1224
Kernel	Uniform

Number of Obs.	370	854
Eff. Number of Obs.	370	854
Order poly. fit (p)	4	4
BW poly. fit (h)	0.350	0.500
Number of bins scale	1	1
Bins Selected	24	18
Average Bin Length	0.014	0.028
Median Bin Length	0.009	0.026
IMSE-optimal bins	24	18
Mimicking Variance bins	39	41
Relative to IMSE-optimal:		
Implied scale	1.000	1.000
WIMSE variance weight	0.500	0.500
WIMSE bias weight	0.500	0.500

```
Number of Obs.                 1224
BW type                       mserd
Kernel                   Triangular
VCE method                       NN

Number of Obs.                  370          854
Eff. Number of Obs.             120          194
Order est. (p)                    1            1
Order bias  (q)                   2            2
BW est. (h)                   0.057        0.057
BW bias (b)                   0.098        0.098
rho (h/b)                     0.588        0.588
Unique Obs.                     206          425

=============================================================================
        Method     Coef. Std. Err.         z     P>|z|      [ 95% C.I. ]
=============================================================================
  Conventional     0.808     0.444     1.820     0.069     [-0.062 , 1.679]
        Robust         -         -     1.866     0.062     [-0.049 , 1.983]
=============================================================================
```

2000-2016

```
Number of Obs.                  384
Kernel                      Uniform

Number of Obs.                  149             235
Eff. Number of Obs.             149             235
Order poly. fit (p)               4               4
BW poly. fit (h)              0.350           0.411
Number of bins scale              1               1

Bins Selected                     9              10
Average Bin Length            0.039           0.041
Median Bin Length             0.020           0.024

IMSE-optimal bins                 9              10
Mimicking Variance bins          15              20

Relative to IMSE-optimal:
Implied scale                 1.000           1.000
WIMSE variance weight         0.500           0.500
WIMSE bias weight             0.500           0.500


Number of Obs.                  384
BW type                       mserd
Kernel                   Triangular
VCE method                       NN

Number of Obs.                  149          235
Eff. Number of Obs.              42           56
Order est. (p)                    1            1
Order bias  (q)                   2            2
BW est. (h)                   0.047        0.047
BW bias (b)                   0.096        0.096
rho (h/b)                     0.490        0.490
Unique Obs.                      97          132

=============================================================================
```

Method	Coef.	Std. Err.	z	P>|z|	[95% C.I.]
Conventional	3.155	0.923	3.418	0.001	[1.346 , 4.964]
Robust	-	-	3.470	0.001	[1.546 , 5.559]

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