THE COST OF A VOTE: EXAMINING LEGISLATIVE INCENTIVES IN AN ELECTION YEAR

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Abstract

Leading up to 2020 elections, North Carolina ended a historically long legislative session in political gridlock and without passing a budget. While a large literature examining voter behavior exists, the impact of legislation passing in an election year on the incumbent party's likelihood for reelection remains poorly understood. We exploit a novel dataset that links the voter affiliation and voter behavior of government workers with state wage increases. A difference-in-difference strategy is applied to a sample of municipal workers who serve as a baseline group to state workers who received wage increases. Movements in voter alignment, relative to the incumbent governor's party, are examined to better understand the incentive of passing or contesting legislation that impacts the large voting block of state employees.

Introduction

There are many different factors that can affect an individual's voting habits. Within these characteristics, we might see an impact on a voter's likelihood to vote for one party or even their likelihood to vote at all. Traditional examples may observe demographic facts about voters such as their race, age, sex, education, and income. Papers such as *Income Inequality and Partisan Voting in the United States* by Gelman, Kenworthy, and Su look at these trends over a long period of time in the U.S. While their results were inconclusive, there are interesting trends examined particularly when looking at the education and income variables. As a generality, it is often shown that richer individuals are more likely to vote Republican, while more educated individuals are more likely to vote Democrat (Gelman, Kenworthy, and Su 2010).

This paper aims to fill the gap in the literature by looking at the effects of a wage increase as a shock to voting habits. Individuals may not actually be shifting in income groups to have an effect that would by strictly an income effect. Instead, this paper would look to see if a wage increase (specifically for state employees) would have a short-term impact on voting habits. If it proves to be correct, it could provide insight into the incentives legislators have when approving changes during or leading up to an election year.

Methods

This paper will address the idea of a wage increase as a shock to voting habits by using the difference in differences method to see the impact of the 2016 raises for state employees in NC. By using Pitt County as a case study for wage increases, we will be able to view the effects of the wage increase on state educators' (ECU faculty and staff) voting habits with a control group of non-educator residents. Stata 16.1 will be used to analyze the data and to run the regression equations.

Difference in Difference

According to a description from Columbia University, "DID is a quasi-experimental design that makes use of longitudinal data from treatment and control groups to obtain an appropriate counterfactual to estimate a causal effect. DID is typically used to estimate the effect of a specific intervention or treatment (such as a passage of law, enactment of policy, or large-scale program implementation) by comparing the changes in outcomes over time between a population that is enrolled in a program (the intervention group) and a population that is not (the control group)" (Columbia).

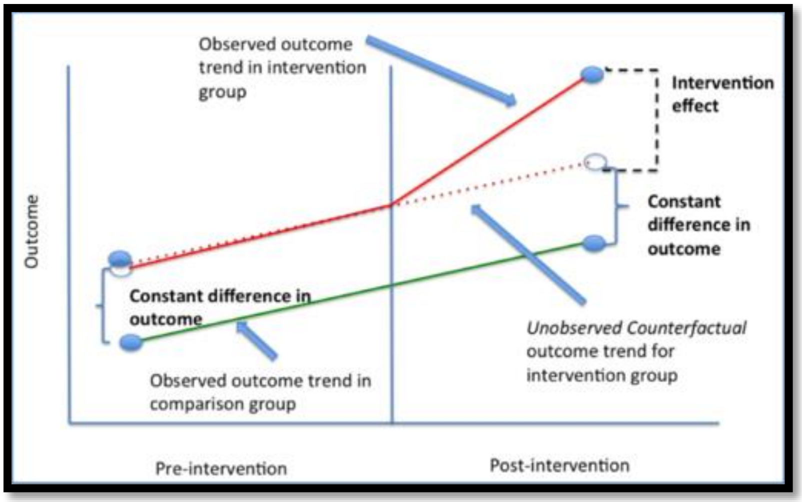

Figure 1 Standard Difference in Difference (Columbia University)

Data Sets

Looking at data from Pitt County, there were 8 different data sets used to create the necessary groups for both control and intervention. The two largest data sets from these were the Pitt County Registered Voter data set and the Pitt County Voter History data set. The other six data sets were for the various different types of employees within the county. These were ECU Faculty and Staff, Greenville Fire and Rescue, Greenville Public Works, Greenville Parks and Rec, Greenville Police, and Pitt County Teachers and Staff. Before the data could be used as one body to analyze the wage increases, they had to be combined to a useable fashion.

The Pitt County Registered Voter data set contains both names and voter registration numbers, while the Pitt County Voter History only contains voter registration numbers and the various employee data sets only contain names. Thus, two different merges were used to put the information together. First, there was a 1:1 merge based on the individual's name with the employee data sets and the Pitt County Registered Voter data set. A 1:1 merge is able to be used here as there should be a specific match to the individual based on their name. While Second, there was a 1:m merge with the Pitt County Voter History data set using voter registration numbers. For this merge, a 1:m merge makes as there will be multiple instances of an individual's voter registration number showing up in the Pitt County Voter History data set to account for them voting on multiple occasions.

These two merges resulted in having the necessary information together, but only as far as the different employee groups were concerned. To put them all back together for regressions, the six different groups were appended. This created a "vertical" stack of information that could then be used. As each group contained a unique group of people, the append function could be successfully used.

Dummy Variables

The typical setup of a difference in difference regression in Stata is:

$$reg\ (dep\ var)\ \ (dummy\ variable)\ \ (second\ dummy\ variable)\ \ (interaction\ term)$$

The results for this come in the form:

$$Y = b_0 + b_1x_1 + b_2x_2 + \ldots. + b_nx_n$$

Where Y = Dependent Variable(DV)

X_1, x_2, x_n – Indepdent Variable(IV)

b_0 – intercept

b_1, b_2 – coefficients

n – No. of observations

Figure 2 Regression Output Formula

While the dependent variable could be a number of different variables (as discussed in the Results section), the two dummy variables and interaction term must be created to represent the shock of the wage increases in 2016. Dummy variables take the value of either 1 or 0 to represent whether or not a certain action has been taken.

The first dummy variable created was the *treatment* variable. This represents the wage increase shock. The 2016 Appropriations Act (HB 1030) was passed on 7/1/16. Therefore, our dummy variable needs to equal 1 for elections that occur after this date. However, all of the elections are referenced in the data with text-based descriptions as seen below.

```
. tab election_desc
```

election_desc	Freq.	Percent	Cum.
03/15/2016 PRIMARY	1,044	5.81	5.81
04/26/2011 SPECIAL ELECTION	9	0.05	5.86
04/30/2019 PRIMARY	424	2.36	8.23
05/04/2010 PRIMARY	1,186	6.61	14.83
05/06/2014 PRIMARY	932	5.19	20.02
05/08/2012 PRIMARY	1,337	7.45	27.47
05/08/2018 PRIMARY	741	4.13	31.60
06/07/2016 CONGRESSIONAL PRIMARY	431	2.40	34.00
06/22/2010 SECOND PRIMARY	240	1.34	35.33
07/09/2019 SECOND PRIMARY	236	1.31	36.65
07/17/2012 SECOND PRIMARY	187	1.04	37.69
11/02/2010 GENERAL	1,666	9.28	46.97
11/03/2009 MUNICIPAL	850	4.73	51.70
11/03/2009 MUNICIPAL ELECTION	1	0.01	51.71
11/03/2015 MUNICIPAL	598	3.33	55.04
11/04/2014 GENERAL	1,384	7.71	62.75
11/05/2013 MUNICIPAL	925	5.15	67.90
11/06/2012 GENERAL	1,800	10.03	77.92
11/06/2018 GENERAL	1,204	6.71	84.63
11/07/2017 MUNICIPAL	494	2.75	87.38
11/08/2011 MUNICIPAL	806	4.49	91.87
11/08/2016 GENERAL	1,460	8.13	100.00
Total	17,955	100.00	

Figure 3 Elections

To get past this issue, I created another variable, *year*, in order to ascribe a numeric year value to each of these different elections. All of the different elections were given a specific year, with the exception being the 11/08/2016 General election as this was the only election to occur after the bill was passed, but before the end of the year. With the *year* variable created, the first dummy variable, *treatment*, could also be created by having it set equal to 1 whenever *year* was 2016.5 or greater.

. tab year

year	Freq.	Percent	Cum.
2009	851	4.74	4.74
2010	3,092	17.22	21.96
2011	815	4.54	26.50
2012	3,324	18.51	45.01
2013	925	5.15	50.16
2014	2,316	12.90	63.06
2015	598	3.33	66.39
2016	1,475	8.21	74.61
2016.5	1,460	8.13	82.74
2017	494	2.75	85.49
2018	1,945	10.83	96.32
2019	660	3.68	100.00
Total	17,955	100.00	

.

tab year treatment

year	treatment 0	1	Total
2009	851	0	851
2010	3,092	0	3,092
2011	815	0	815
2012	3,324	0	3,324
2013	925	0	925
2014	2,316	0	2,316
2015	598	0	598
2016	1,475	0	1,475
2016.5	0	1,460	1,460
2017	0	494	494
2018	0	1,945	1,945
2019	0	660	660
Total	13,396	4,559	17,955

Figure 4 Intermediary Dummy Variable (Year)

The second dummy variable to be created is *state_worker*. Among our data sets, ECU faculty and staff are our group of state workers This variable was quite easy to create after some searching through the data. The ECU Faculty and Staff data set had a unique identifier variable, *ECU*. At first glance, it looked like this could have been used as our dummy variable without alteration, but the *ECU* variable only had the positive value of 1 for each member of the data set. Therefore, it wouldn't be able to be used to look at the rest of the employees in the appended data set as easily. I created a second dummy variable *state_worker* to have the distinction very clear for future regressions and data manipulation.

. tab treatment

treatment	Freq.	Percent	Cum.
0	13,396	72.10	72.10
1	5,185	27.90	100.00
Total	18,581	100.00	

Figure 6 Dummy Variable One (treatment)

. tab state_worker

state_worker	Freq.	Percent	Cum.
0	17,226	92.71	92.71
1	1,355	7.29	100.00
Total	18,581	100.00	

Figure 5 Dummy Variable Two (state_worker)

The final step in creating variables to run the DID regression was to create the interaction term between the two dummy variables. This was done by simply setting the *interaction_term* variable equal to *treatment* x *state_worker.*

Expected Results

At the conclusion of our DID analysis, we expect to see that state workers will be more likely to vote in favor of the party that approved the 2016 wage increases (Governor's party) than they were before the wage increase. In addition to this, there is likely to be some amount of spillover to other residents in that are amiable towards educators and other state employees. This will be seen in our examination of the control group of non-educator residents.

Additional results to be expected is that there will be a higher voter turnout after the proposed wage increases to represent residents interested in supporting further wage increases. However, there is some negative relationship implied here, as mentioned in *Employment, Wages, and Voter Turnout* by Charles and Stephens. As a resident's wage increases, so does their opportunity cost for going out to vote as there is more associated value with them staying at work (Charles and Stephens 2011). With that said, the wage increases are more likely to cause a short-term shock and thus will not create the same sort of income effect.

Results

Analysis of Individuals who Voted Republican (Governor's Party)

After first approaching this topic, I realized that I had made a mistake in my assumptions. It had looked like the wage increase resulted in voters following the anticipated result of voting in favor of the party who had approved the wage increase. However, the wage increase was passed in July, 2016. Gov. Cooper was elected in 2016, but he didn't take office until 2017. With a Republican majority in both the House and Senate at the time, this means that the wage increases came from a largely Republican appropriations bill. In fact, not a single Republican voted against the bill in its passage 91-22.

Adjusting our regression to have new variables for *voted_rep* and a new interaction term, we get the results shown below. What you'll see in these regressions, as opposed to the one illustrated in the next section looking at unaffiliated voters who voted Democrat, is that all of our variable coefficients are negative. We're showing that after the timeline of our shock, you're having fewer unaffiliated state workers voting Republican. These results are not what we expected when thinking about the issue intuitively. It would make sense for there to be an increase in support for the party that made the wage increases, but that was not the case. Some examples of explanations for this will be discussed in the conclusion below.

```
. reg voted_rep treatment state_worker interation_term_rep if party_cd=="UNA"

      Source |       SS           df       MS      Number of obs   =     3,228
-------------+----------------------------------   F(3, 3224)      =     57.34
       Model |  26.8938012         3  8.96460039   Prob > F        =    0.0000
    Residual |  504.041763     3,224  .156340497   R-squared       =    0.0507
-------------+----------------------------------   Adj R-squared   =    0.0498
       Total |  530.935564     3,227  .164529149   Root MSE        =     .3954

------------------------------------------------------------------------------
   voted_rep |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   treatment |   .1200542   .0172215     6.97   0.000      .086288    .1538204
state_worker |  -.0363746   .0324007    -1.12   0.262    -.0999025    .0271534
interation_term_rep |  -.2659786   .0398162    -6.68   0.000    -.3440463   -.1879109
       _cons |   .2092141   .0092053    22.73   0.000     .1911653    .2272629
------------------------------------------------------------------------------
```

Figure 7 voted_rep Regression

Regression in Favor of Democratic Party

As mentioned above, the initial regressions run mistakenly looked at the Democratic Party. While the party in control at the time of the wage increase was the Republican Party, there is still information to be learned by looking at how voters responded to the shock in relation to the Democratic Party (which many educators are affiliated with).

Like the regression looking at the Republican Party, this regression restricted the regression to voters who were registered as “unaffiliated.” This helps control for existing biases and to look at what sort of effect the wage increase would have on “unaffiliated voters. This regression’s results lined up much better with our anticipated results. With a positive .133358 coefficient for the *interaction_term* variable. This means that roughly 13% of unaffiliated members of ECU faculty and staff voted for the Democratic party after the wage increases of 2016. As the shock to the system is more likely to affect unaffiliated voters, this makes sense to see a better fit to our model. However, despite this matching our expected results, it is incorrect for the shock that we are trying to measure.

```
. reg voted_gov treatment state_worker interaction_term if party_cd=="UNA"

      Source |       SS           df       MS      Number of obs   =     3,228
-------------+----------------------------------   F(3, 3224)      =    216.30
       Model |  123.052974         3  41.017658   Prob > F        =    0.0000
    Residual |  611.377014     3,224  .189633069   R-squared       =    0.1675
-------------+----------------------------------   Adj R-squared   =    0.1668
       Total |  734.429988     3,227  .227589088   Root MSE        =    .43547

----------------------------------------------------------------------------------
       voted_gov |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+----------------------------------------------------------------
       treatment |  -.3184282   .0189667   -16.79   0.000    -.3556163   -.2812401
    state_worker |  -.3084914   .0356841    -8.65   0.000    -.3784573   -.2385256
interaction_term |    .133358   .0438512     3.04   0.002      .047379    .2193371
           _cons |   .5121951   .0101382    50.52   0.000     .4923172     .532073
----------------------------------------------------------------------------------
```

Figure 8 Regression 2 (Unaffiliated)

Conclusion/Why It Matters

This issue matters because of the implications it has should there be a direct relationship between legislative policy on wage increases and voter turnout/voting behavior. While there are certainly a great deal of factors that contribute to an individual’s voting habits, this one is of particular importance as it represents legislator’s ability to “buy” votes by altering their legislative behavior during election years. Furthermore, it is important to look at whether any effects from these changes stay localized within that particular year, or if there is a spillover effect to be seen for a period of time after the income shock.

Looking at our results, we didn’t see what we expected to happen. As mentioned above, the intuitive thought is that there would be an increase in support for the party behind the wage increase. This was not the case. Does it mean that there isn’t validity to the idea? Not necessarily, as there are a number of factors that could create a separate shock to the voting system. Furthermore, educators have a tendency to lean Democrat in general, so there could be an inherent bias even on the unaffiliated voters.

Wage Increase Timeline

While there have been a number of raises for state employees and teachers over time, it is important to look at when a number of these raises fell. There are specific amount raises that have occurred in the off years, but when looking percentage increases from the past 10 years or so, we see standouts in 2008 and 2012, in addition to the discussed increases in 2016. With 2008 and 2012 being election years, and notably there being no raises in the four years between them, it would seem that legislators have seen wage increases as an incentive to voters, even if our sample didn't show it. If we view educators as individuals who do have a bias towards Democrats, it would seem that the wage increases consistently falling on election years would be an effort by a Republican-controlled House and Senate to gain votes.

LEGISLATIVE SALARY INCREASES

YEAR	STATE EMPLOYEES	TEACHERS
1999-00	1% COLA + 2% career growth + $125 compensation bonus	4% - 11%
2000-01	2.2% COLA + 2% career growth + $500 compensation bonus	2.5% - 13.8%
2001-02	$625	1% - 6.92% (2.86% average)
2002-03	-0-	0% - 5.85% (1.84% average)
2003-04	$550 one-time bonus	1.42% - 5.86% (1.81% average)
2004-05	Greater of a $1,000 or 2.5% across-the-board increase	1.41% - 5.9% (2.5% average)
2005-06	Greater of a $850 or 2% across-the-board increase	1.77% - 6.27% (2.24% average)
2006-07	5.5% across-the-board increase	6.45% - 14.05% (8.23% average)
2007-08	4% across-the-board increase	4.05% - 9.53% (5% average)
2008-09	Greater of $1,100 or 2.74% across-the-board increase	2.39% - 6.63% (3% average)
2009-10	-0-	-0-
2010-11	-0-	-0-
2011-12	-0-	-0-
2012-13 [d]	1.2% across-the-board increase	1.2% across-the-board increase
2013-14	-0-	-0-
2014-15 [e]	$1,000 for State employees	0.5% - 18.5% (7% average)
2015-16 [f]	-0- + $750 compensation bonus	0 - 9.6% + $750 compensation bonus (3.8% average)
2016-17 [g]	1.5% increase + 0.5% compensation bonus Funding for merit bonuses	0% - 13.1% (4.7% average)
2017-18 [h]	$1,000 salary increase	0.6% - 6.9% (3.3% average)
2018-19 [i]	Greater of 2% salary increase or increase to $31,200 salary for State agency employees	0% - 14.8% (6.5% average)

Figure 9 Wage Increase Timeline

House Bill 2

When looking at our results, we see that there was a positive result with individuals voting more for Democrats after the 2016 mark. If this still served as a shock in the voting pattern, it begs the question of what is the correct shock if the wage increase does not line up with it. That is, was there another event in 2016 that could have had a larger effect on voting behavior than the wage increase. My proposed answer to this is House Bill 2. House Bill 2 (Public Facilities Privacy and Security Act) was passed in March, 2016. This means that it would fall in the same timeline for everything from our initial regression, except for the June, 2016 Congressional Primary. The fallout of HB2 was a lot of negative feedback on both NC and the Republican party based in NC. Given the nature of this bill and its effect on many students at the time, it’s likely that many educators would have felt strongly on the subject and may have cast their votes against it in the upcoming election. In fact, we saw Gov. Cooper use the fallout of HB2 as part of his campaign that led to his victory over the incumbent, Pat McCrory. With this line of reasoning, it would make sense for the Republicans to have offered the raises within the Appropriations Act as a way to try and keep some of the swing voters in their favor.

Research Moving Forwards

While the regressions run did not match our expected results, they did seem to indicate some spillover effect onto voters who were not directly affected by the wage increase. Moving forwards, work could be done to pinpoint this spillover effect to see what the nature of it is. Looking at why impacted voters did not vote in favor of the party who passed the wage increase, it is possible that the wages were not as much as they would have liked. Additional reasons for our results could be voters of a particular party voting strategically in the opposite primary. It also brings up the question regarding our sample of Pitt County and how well the state employees in this county are representative for the state.

A couple things that can be done in the future to look at this effect further would be to look at another county's data. With enough different counties' data, we could see a more generalized effect. The main importance with this sort of testing going forwards would be sure that the same type of workers are included from each county so as to not introduce additional biases.

Another idea for moving forward would be to adjust our shock point to previous election years. Seeing as there were similar wage increases in 2008 and 2012, it would be interesting to see how the measured effect of a wage increase changed from election year to election year. This would also let us view the effect more broadly as voting for an incumbent in general as opposed to a party. The regressions in this study had to be viewed from a party standpoint as the party of the incumbent shifted during the timeframe of the data. By shifting the shock points, we could see if there was a difference in support of wage increases based on which party was approving the wage increases.

2020 Elections

Looking at the patterns from the past three elections and given the drawn-out nature of the current political atmosphere, it would be reasonable to predict that we would see another set of raises passed within the next appropriations bill. This would match up with the pattern we have observed and aid a Republican effort to unseat Gov. Cooper. The only caveat to this prediction is that with the Covid-19 pandemic, you may see funds distributed in different ways to try to help with the relief efforts. This will provide a huge shock to the upcoming elections, especially as the various parties take actions to help deal with the consequences of the situation. As the budget is passed, we will have the opportunity to see real time whether there is a legislative effort to sway unaffiliated state workers in favor of the House and Senate majorities, if not in the direction of the governor.

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