ECON 3161

Economic Patterns in Voting

By Robert L. Bland and S. Grace Little

After the controversial election of 2016, many questions were left unanswered by traditional polling and prediction standards. Our paper aims to examine economic and demographic behaviors that drive voting patterns in three key Rust Belt states. After examining several pivotal works, we describe their contribution to the literature, and explain how our work will contribute to the research discussed. We then proceed to examine American Community Survey data for years predating general elections in the three pivotal states – Illinois, Wisconsin and Pennsylvania – examining each at the county level. Our results suggest several important factors in voter decisions, especially when examining the interactions between demographic factors and economic factors. Consequently, we find that while economic factors may be significant in voter decisions, they may not be key in voter decisions

Student
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On November 8th, 2016, a popular poll model run by FiveThirtyEight politics solidified their predictions for the 2016 Presidential Election. The model was considered substantially more favorable to Donald Trump's chances, holding him at a 28.6% chance of taking the presidency on the eve of the election. Several other models held the odds much lower, with some going as low as giving Mr. Trump a 1% chance of taking the presidency. On November 9th, 2016, Americas went to the polls and elected a new president, and against most odds, they chose President Donald Trump.

Electoral modeling and statistical analysis is incredibly fraught. There are hundreds of possible factors, thousands of polls, and millions of voters that all combine to make the run up to any presidential race both interesting and difficult to predict. However, the 2016 presidential cycle saw a candidate that defied almost every reputable poll and model. There are several possible causes for this – some have reported the rise of an electorate not reached by traditional polling or flaws in the current election system. However, we hypothesize that there may be a more basic explanation. We believe that a combination of population, economic and ethnic factors can be correlated to a rise in vote for the non-incumbent party, which in the 2012 and 2016 election was the Republican (GOP) Party.

To reach this hypothesis, we examined several papers with important pertinence to our topic. We closely examined two pivotal works on election politics - *Abhor the Event: Voting Patterns and the Rise of Trump* by Michael Gobel, *and Voting for Growth, Fairness, or Inequality? Class-Biased Economic Voting in Comparative Perspective*, by Timothy Hicks, Alan M. Jacobs and J. Scott Matthews.

The 2016 election cycle was such a discontinuation from the norm that traditional modes of analysis are proving to be inadequate. The traditional narrative of the 2016 election pivoted around three features: Racial divide, economic inequality, and the sharp divide between candidates' personalities. One of the first analytical narratives after the election, *Abhor the Event: Voting Patterns and the Rise of Trump* disagrees with the traditional narrative. According to the author, a large portion of the voting base had essentially "locked in" their vote through the party system alone, leaving only around 4-9% of eligible voters open to hearing from the candidates before they made their choice. That voting bloc carried with them a few key traits that allowed Trump to emerge as president. The first was a resounding response to Trump's call to return America to an idealized past. Primarily low-income families were the ones who sought this "Great America", and those who make $30,000 or less a year voted for Trump at a 16-point swing to Mitt Romney in 2012. The second determining factor was voter apathy versus voter enthusiasm. While early voting was at an all-time high, only 55.4% of eligible voters cast their ballot, a 20-year low. Donald Trump was largely seen as the candidate more likely to attract enthusiastic support, compared to Clinton's sterner demeanor, and thus was able to pull the necessary voters. Finally, author Michael Goebel argues that many voter had preemptively chosen candidates and adjusted their own fears to justify their decision. From *Abhor the Event: Voting Patterns and the Rise of Trump* we can determine that the essential bloc strongly held onto a stylized version of America's past. While it would be impossible to see what that means for every voter, we can examine past to see how we got here in the first place and apply these explanations to our model.

When trying to predict the future outcome of elections, the past offers an effective tool for determining the odds. In *Voting for Growth, Fairness, or Inequality? Class-Biased Voting in Comparative Perspective*, economists Timothy Hicks and Alan Jacobs measures how voters factor economic growth and fairness into voting habits. Hicks and Jacobs found that voters try and vote in an economically moral manner, but often find they must make trade-offs and that their decisions are not always the most informed. The study measured the incumbent's likelihood of winning the election compared to the economic growth and prosperity of different economic classes. From that data point, the responsiveness in voting to economic growth was measured between the bottom 20%, middle class, and top 5% income brackets. What was found from the data suggested that economic growth in the top 95th percentile had a substantially higher amount of influence into predicting voting patterns compared to the economic growth in other income brackets. When normalizing factors such as race, religion, and gender, voters in the bottom 20% are actually more reactive to change their voting habits depending on the economic growth of the top 5%, not their own bottom 20%. The median middle class group behaved as one might expect: growth within the middle class during the incumbent's term increased their likelihood of reelection. Growth in the top 5% also increased likelihood of reelection by the middle class, but to a lesser effect compared to the bottom 20%. The voters in the top 5% were the most reactive to economic growth when adjusting voting habits. This paper suggests that the influence of the wealthiest actually changes how the rest of society votes. This implies that while many believe they are working for their own self-interest, they are actively reacting to economic situations that have no effect on their lives. In many regards, this suggests that the media is to blame because of their inadequate coverage of economic issues that affect the average voter. Additionally, this may suggest that examining overall economic welfare in a county may not be a strong predictor of the vote direction. In the end, the irrationality of voters might be stronger than traditional models have thought, especially for the high-energy 2016 election.

We aim to contribute to the literature in several ways. Firstly, by examining county data in three key states, we hoped to identify key factors at a local level. This could be anything from an aging population to an increasing in countywide unemployment. Secondly, by examining our voter data as county-by-county, we hope to highlight the voting patterns of both rural and urban voters, who may have vastly different morals and opinions on the issues. Thirdly, we wanted to highlight key factors that could be predictors of voting patterns in future elections.

All data comes from the American Community Survey, accessed through the American Fact Finder Database, and compiled using their adjustable tables. By using officially compiled data, we believe that we are getting the best quality of data that is available to the public. Our voter data was compiled by three separate entities for the three Rust Belt states of study. In Illinois, we used the Illinois State Board of Elections 2012 General Election Official Vote Totals Book and the Illinois State Board of Elections 2016 General Election Official Vote Totals Book. In Pennsylvania, data was compiled from the Pennsylvania Department of States 2012 Presidential Elections Official Returns, sorted by President of the United States by County and the Department's 2016 Presidential Elections Official Returns, sorted by President of the United States by County. Finally, in Wisconsin our data was gathered from the Wisconsin Elections Commission's 2012 Fall General Election Results and 2016 Fall General Election Results.

In compiling our research, we have decided to address several factors that may influence voting choice and the direction in which to vote. We began with a simple way to divide the electorate - Age. Age and voting patterns have instinctual correlation – one could reasonably assume that the higher the median age in an area, the more likely the area will vote Republican.

We have chosen age as a parameter in order to prove the concept that older voters tend to vote in more conservative trends, which for our regions would be part of the Republican vote. Additionally, we chose age to highlight a common fear of blue-collar voters. The fear of jobs leaving an area can validated and measured by the amount of young people (between 18 and 30) living in an area. This can directly cause a voter to consider a more conservative vote, in an effort to return their economic situation to that of days gone by.

When we analyzed our age measurement (agechange, Figure 1), the result was surprising. We found that within our full regression model (Figure 2):

$$republicanvotechange = \beta_0 + \beta_1 incomechange + \beta_2 unemploychange + \beta_3 nonwhitechange + \beta_4 agechange + \beta_5 popchange + u$$

age was a surprisingly insignificant factor. With a coefficient of .1104 and a t-stat value or -2.43 (Figure 6), we decided to run additional models to discover if there was a model in which age would be a more powerful factor.

Our next non-economic factor of study was ethnicity. Ethnicity is often either over-hyped or under-valued when examining voter patterns. This could be because ethnic voters are a varied and underrepresented group in American politics. While diving into the nuances of their vote is not our primary goal, we did aim to prove that ethnic voters tend to vote for a liberal (blue) candidate, which in our region of study translates to a non-republican vote.

Again, using original full-regression model (Figure 2):

$$republicanvotechange = \beta_0 + \beta_1 incomechange + \beta_2 unemploychange + \beta_3 nonwhitechange + \beta_4 agechange + \beta_5 popchange + u$$

we found that a change in the nonwhite proportion of the population of a county (nonwhitechange, Figure 1) was a significant factor. With a coefficient of -.2130 and a t-stat of -2.43 (Figure 6), we found that for every 1% increase in non-white population, our county would be less likely to vote Republican by .213%. This confirmed our suspicions that as an area became more ethnically diverse it would be more likely to vote for a non-Republican candidate.

For our final demographic variable, we considered population change (popchange, Figure 1). We hypothesized that in areas where population decreased, voters would be more likely to yearn for a more conservative leader, and vote for a Republican candidate.

Using our full-regression model (Figure 2):

$$republicanvotechange = \beta_0 + \beta_1 incomechange + \beta_2 unemploychange + \beta_3 nonwhitechange + \beta_4 agechange + \beta_5 popchange + u$$

we found that a change in population was a statistically significant factor (t-stat: 2.08), although it was a weak correlation with a coefficient of -0.3937 (Figure 6).

After examining our non-economic factors, we decided to regress a second model, to explore whether these non-economic factors would be more significant. We used a second regression model of only non-economic factors, represented by the equation below (Figure 3):

$$republicanvotechange = \beta_0 + \beta_1 nonwhitechange + \beta_2 agechange + \beta_3 popchange + u$$

This model, while interesting to examine, confirmed most of our previous expectations. We found that each variable was still statistically insignificant and only weakly correlated.

At this point, we moved on to our economic factors. We began by examining unemployment rates by county for the areas of study. Instinctually, we believe that higher than average unemployment rates translate to dissatisfaction with the existing party in power. This could lead to higher rates of "protest" votes, which in our areas would translate to a Republican vote. A county's unemployment rate is one of our key independent variables. Using our full regression analysis (Figure 2)

$$republicanvotechange = \beta_0 + \beta_1 incomechange + \beta_2 unemploychange + \beta_3 nonwhitechange + \beta_4 agechange + \beta_5 popchange + u$$

we saw that a change in unemployment (unemploychange, Figure 1) was statistically significant with a t-value of 3.42, and heavily weighted with a coefficient of 0.3132 (Figure 6).

Our next factor of study was a change in income. Instinctually, we believed that as income would increase in an area, the tendency to vote for a more fiscally conservative candidate would cause an increase in Republican votes. Using our full regression analysis (Figure 2):

$$republicanvotechange = \beta_0 + \beta_1 incomechange + \beta_2 unemploychange + \beta_3 nonwhitechange + \beta_4 agechange + \beta_5 popchange + u$$

We saw that a change in income (incomechange, Figure 1) was statistically significant with a t-value of -2.49, and heavily weighted with a coefficient of -.3109 (Figure 6).

Because we had already regressed a model highlighting only non-economic factors, we decided to create a model for our economic factors alone. Using the equation (Figure 4):

$$republicanvotechange = \beta_0 + \beta_1 incomechange + \beta_2 unemploychange + u$$

we saw that this model confirmed our previous findings. We found that both income change and unemployment change were significant (t-stat: .2.58 and 2.44, respectively) and heavily correlated (coefficients of -.3357 and .2152, respectively) (Figure 6).

After examining all of our data, we decided to run a final regression omitting our weakest variable – age. Using the formula below (Figure 5):

$$republicanvotechange = \beta_0 + \beta_1 incomechange + \beta_2 unemploychange + \beta_3 nonwhitechange + \beta_4 popchange + u$$

we found that without the age factor, t-stat values for each variable increased, indicating an increase in significance. We decided to run one of the regression models without age because the t statistic in the full regression indicated that age was not statistically significant. While the other t stat values increased, this model did have a slightly lower R^2 (.2885) than the full regression (.2891)

For each model, we also examined our R^2 values to ensure that we were reaching a line of good fit. The inclusion of more variables increased our R^2 for every model, which meant our model became more accurate at predicting voting habits as we shifted it. The model summary statistic (Figure 6) shows the comparison between the models and improvement of R^2. Model 1 includes only economic factors in the model, and the fit of R^2 is only .1727. Model 2 includes all non-economic factors and has an even lower R^2 of .0756. When we combine the factors, the regression starts to vastly improve. Model 3 contains all statistically significant variables and has a R^2 of .2885. Our final model, which contains all five independent variables, has the greatest R^2 of .2891. The progressive improvement of our R^2 tells us that the model continues to improve its predictive accuracy. One issue with this regression is that R^2 never goes higher than .3, which means that the predictive values of our regression are strong but not ironclad. This is explained by the complexity of voting behaviors as an area of study, and the inability to tie votes to a single factor. The greater amount of non-related variables we can add into the equation, the more accurate our regression will become. The double of R^2 between model 1 (R^2 =.1727) and model 4 (R^2 =.2891) shows us that non-economic factors are extremely relevant in predicting voter behavior and that the greater we account for those factors, the more accurate our economic predictive variables become.

When examining the collinearity between our variables, several things stood out. Firstly, in our covariance table, values were very close to zero, indicating that there was no very little to no linear relationship between variables. Our correlation table was also encouraging. With low values for each relationship, we were able to successfully state that our variables were not correlated, indicating that we had already partially met Gauss-Markov assumptions.

When ensuring that our model met Gauss-Markov assumptions, we examined several factors. The First Gauss-Markov assumption states that the model needs to be linear in its parameters. This assumption was met for our models, as shown in Figure 6. The second Gauss-Markov assumption states that sampling must be random in nature. While we focused on three states in the Rust Belt of the United States, we examined all of the counties within those states, allowing for a larger sample size. In addition, our independent variables were gathered from the American Community Survey, which collects data from randomly selected individuals and has held up to scrutiny for several years of use. Because the ACS is an institutional standard, it is safe to assume that we can state that the second Gauss-Markov assumption is met.

The third Gauss-Markov assumption is that there is no perfect collinearity. Our analysis in Figure 7 clearly states that there is no perfect collinearity between variables, allowing us to state with conviction that we have met the third Gauss-Markov assumption.

The last two Gauss-Markov assumptions both deal concern the error term *u.* The fourth Gauss-Markov assumption states that our data will produce a 0-conditional mean, meaning that our error term *u* will have an expected value of zero for any values of our independent variables. The final Gauss-Markov assumption deals with homoskedacity. Because we are unable to ensure that these last two assumptions have been followed, we mitigate potential problems by running multiple regressions with multiple variables, which are intended to reduce any potential bias.

As previously stated, the double of R^2 between model 1 (R^2 =.1727) and model 4 (R^2 =.2891) shows us that non-economic factors are extremely relevant in predicting voter behavior and that the greater we account for those factors, the more accurate our economic predictive variables become. If provided the opportunity for further research, we would want to focus on these non-economic factors, and possibly expand our study to include less definite measures, perhaps in the areas of morality or religion, to continue to improve our model. We would also break our gender and ethnic distributions into detail, and possibly examine candidate approval ratings published by independent parties, or even polling data for each candidate.

After completing our data analysis, we were able to come to several conclusions about voting patterns in the Rust Belt states of Pennsylvania, Illinois and Wisconsin. While voter behavior is notoriously tricky to predict, and there is no one factor that will cause someone to vote in a certain way, we were able to conclude that while economic variables (change in income and change in unemployment rate) were significant, they were more useful when examined with certain non-economic variables (change in ethnicity, change in age, and change in population). This highlights the tricky nature of voter prediction, and the nebulous nature of polling. While our study did not definitively prove that a change in economic situation would cause a change in voter choice, we did come to several important revelations concerning the nature of noneconomic factors and economic factors, and their relation to voting preference.

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Appendix

To note: The coefficients of the regression models equate to the following: Each independent variable is the change of that factor from 2011-2015 as a percent, and the coefficient is amount of percent change that would occur with x change in percent of the independent.

Figure 1: Summary Statistics Table

Variable	Obs	Mean	Std. Dev.	Min	Max
County	241	121	69.7149	1	241
pop2011	161	180945.6	453955	4262	5182969
pop2015	161	182863.5	459483	4451	5236393
popchange	161	.0289329	.4271976	-.8393	5.3457
mediana~2011	112	39.93929	3.656251	28.4	49.4
mediana~2015	161	41.96832	4.508262	29.3	52.6
agechange	112	.0234295	.0245158	-.0765	.1463
seXratio2011	161	99.95776	8.958694	89	193.2
seXratio2015	161	100.8491	14.59028	89.5	273.4
seXratioch~e	161	.0066342	.0349927	-.0519	.4151
nonwhite2011	211	.0838588	.0939983	.0094	.8417
nonwhite2015	211	.0870194	.0976532	.0056	.869
nonwhitech~e	211	.0420213	.1846686	-.6442	.724
unemploy2011	213	7.226413	3.709561	.056	17.2
unemploy2015	213	4.690526	2.472514	.036	9.9
unemploych~e	213	-.3397681	.0987478	-.5465	.0375
income2011	113	42359.93	12449.92	20465	85976
income2015	113	41050.65	11541.74	21815	86264
incomechange	113	.0079451	.0863875	-.1505	.2738
republi~2012	241	54.59129	10.57577	13	78
republi~2016	241	60.90415	12.16618	15.5	84.3
republican~e	241	.1187635	.1074407	-.1832	.6154

Figure 2: Full Regression

$$republicanvotechange = \beta_0 + \beta_1 incomechange + \beta_2 unemploychange + \beta_3 nonwhitechange + \beta_4 agechange + \beta_5 popchange + u$$

```
. reg republicanvotechange incomechange unemploychange nonwhitechange agechange popchange
```

Source	SS	df	MS
Model	.251094266	5	.050218853
Residual	.617391273	75	.008231884
Total	.868485538	80	.010856069

Number of obs	=	81
F(5, 75)	=	6.10
Prob > F	=	0.0001
R-squared	=	0.2891
Adj R-squared	=	0.2417
Root MSE	=	.09073

republicanvo~e	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
incomechange	-.3108594	.1246722	-2.49	0.015	-.5592192	-.0624996
unemploychange	.3132286	.0916057	3.42	0.001	.1307408	.4957165
nonwhitechange	-.2130992	.0876666	-2.43	0.017	-.3877401	-.0384584
agechange	.1104751	.4477908	0.25	0.806	-.7815699	1.00252
popchange	-.0393793	.0189028	-2.08	0.041	-.0770356	-.0017231
_cons	.166469	.0347471	4.79	0.000	.0972493	.2356887

Figure 3: Non-Economic Factors

$$republicanvotechange = \beta_0 + \beta_1 nonwhitechange + \beta_2 agechange + \beta_3 popchange + u$$

```
. reg republicanvotechange nonwhitechange agechange popchange
```

Source	SS	df	MS
Model	.065646788	3	.021882263
Residual	.802888476	78	.010293442
Total	.868535264	81	.010722658

Number of obs	=	82
F(3, 78)	=	2.13
Prob > F	=	0.1037
R-squared	=	0.0756
Adj R-squared	=	0.0400
Root MSE	=	.10146

republicanvo~e	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
nonwhitechange	-.0641171	.0911598	-0.70	0.484	-.2456023	.1173682
agechange	.0764703	.5001176	0.15	0.879	-.9191873	1.072128
popchange	-.0462575	.0210659	-2.20	0.031	-.0881964	-.0043186
_cons	.0432422	.0149832	2.89	0.005	.013413	.0730714

Figure 4: Purely Economic Factors

$$republicanvotechange = \beta_0 + \beta_1 incomechange + \beta_2 unemploychange + u$$

```
. reg republicanvotechange incomechange unemploychange
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Source	SS	df	MS
Model	.16194732	2	.08097366
Residual	.775916626	82	.009462398
Total	.937863946	84	.011165047

Number of obs	=	85
F(2, 82)	=	8.56
Prob > F	=	0.0004
R-squared	=	0.1727
Adj R-squared	=	0.1525
Root MSE	=	.09727

republicanvo~e	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
incomechange	-.3357146	.1302214	-2.58	0.012	-.5947665	-.0766628
unemploychange	.2152133	.0883501	2.44	0.017	.0394567	.3909698
_cons	.1271963	.0309262	4.11	0.000	.0656742	.1887183

Figure 5: Regression Analysis without Age

$$republicanvotechange = \beta_0 + \beta_1 incomechange + \beta_2 unemploychange + \beta_3 nonwhitechange + \beta_4 popchange + u$$

```
. reg republicanvotechange incomechange unemploychange nonwhitechange popchange
```

Source	SS	df	MS
Model	.250593219	4	.062648305
Residual	.617892319	76	.008130162
Total	.868485538	80	.010856069

Number of obs	=	81
F(4, 76)	=	7.71
Prob > F	=	0.0000
R-squared	=	0.2885
Adj R-squared	=	0.2511
Root MSE	=	.09017

republicanvo~e	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
incomechange	-.3097923	.123825	-2.50	0.015	-.5564111	-.0631735
unemploychange	.3134389	.091034	3.44	0.001	.132129	.4947488
nonwhitechange	-.2083147	.0849648	-2.45	0.017	-.3775368	-.0390927
popchange	-.0373253	.0168653	-2.21	0.030	-.0709156	-.0037351
_cons	.1684479	.033599	5.01	0.000	.1015297	.2353662

Figure 6: Model Summaries

	Model 1 (economic)	**Model 2 (non-economic)**	**Model 3 (Age restricted)**	**Model 4 (Full regression)**
Number of observations	85	82	81	81
Income change	-.3357 t-stat: -2.58		-.3098 t-stat: -2.5	-.3109 t-stat: -2.49
Unemployment change	.2152 t-stat: 2.44		.3134 t-stat: 3.44	.3132 t-stat: 3.42
Nonwhite change		-.0641 t-stat: -.70	-.2083 t-stat: -2.45	-.2130 t-stat: -2.43
Age change		.07647 t-stat: .15		.1104 t-stat: .25
Population change		-.0462 t-stat: -2.20	.0373 t-stat: -2.21	-.03937 t-stat: -2.08
Intercept	.1271 t-stat: 4.11	.0432 t-stat: 2.89	.1684 t-stat: 5.01	.1665 t-stat: 4.79
R-squared	.1727	.0756	.2885	.2891

Figure 7: Collinearity Table

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. vce

Covariance matrix of coefficients of regress model
```

e(V)	incomech~e	unemploy~e	nonwhite~e	agechange	popchange	_cons
incomechange	.01554317					
unemploych~e	.0024181	.0083916				
nonwhitech~e	.00131727	-.00250888	.00768543			
agechange	-.00193679	-.00038166	-.00868407	.20051661		
popchange	-.00010245	.00009021	.00002352	-.00372812	.00035731	
_cons	.00029181	.00290738	-.00110173	-.00359184	.00008813	.00120736

```
. vce, corr

Correlation matrix of coefficients of regress model
```

e(V)	income~e	unempl~e	nonwhi~e	agecha~e	popcha~e	_cons
incomechange	1.0000					
unemploych~e	0.2117	1.0000				
nonwhitech~e	0.1205	-0.3124	1.0000			
agechange	-0.0347	-0.0093	-0.2212	1.0000		
popchange	-0.0435	0.0521	0.0142	-0.4404	1.0000	
_cons	0.0674	0.9134	-0.3617	-0.2308	0.1342	1.0000