Higher Turnout Rate For Competitive Election Districts in BC

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Summary

The aim of the project is to determine if there is a correlation between voter turnout and the competitiveness of an election district. Specifically, we look at elections occurring in British Columbia between 2005 and 2017. We hypothesized at the beginning of this project that we would find a correlation between the two variables. With our hypothesis in place, we set a threshold of 0.05 as our probability of committing a Type I error and we refer to this value as α.

To test our hypothesis, we decided to examine a two-sided Pearson correlation test. Assumptions of the Pearson correlation test were checked and found to be valid; therefore, we followed through with the test and found a p-value given by $p < .001$ and a correlation of 0.27. Based on $p < \alpha$ we can say that there is a statistically significant association between voter turnout and competitiveness. We have defined our competitiveness variable so that the correlation is a positive correlation.

Introduction

In the past 2020 US election, it was reported that the voter turnout rate was substantially higher in battleground states than spectator states ("Voter Turnout Is Substantially Higher in Battleground States Than Spectator States" 2020). We are interested to know if a similar pattern was also observed in the provincial elections of British Columbia in the past few years. Therefore, in this data analysis project, we work with publicly available data sets to answer the following inferential question:

> Are close elections correlated with higher voter turnout?

To answer this question, we have used two publicly available data sets from the BC government; provincial voter participation (Elections BC 2018a) and provincial voting results (Elections BC 2018b). These are referred to as pvp and pvr respectively throughout the project repository. More details about the data can be found in the "Data" section of this report. These data sets give us the opportunity to investigate the relation between the share difference in votes between the winner and the runner-up and the turn out at different electoral districts for several years.

Subsequently, we investigate the relationship between the following two variables measured at the level of the electoral district (ED): voter turnout rate and the competitiveness of a race. The voter turnout rate is calculated as the number of valid votes cast divided by the number of registered voters in an ED for a given election. An electoral district's competitiveness is calculated as the negative difference in share of the votes between winner and runner-up. The smaller magnitude of competitiveness variable is an indicator of closer/ more competitive election. We will use a two-sided Pearson correlation test via `cor.test()` in R with the following hypotheses:

> **Null Hypothesis:** The correlation coefficient between the voter turnout rate and the race competitiveness is equal to zero.
>
> **Alternative Hypothesis:** The corrrelation coefficient between the voter turnout rate and the race competitiveness is not equal to zero.

Our Type I error will be set at alpha = 0.05. We expect this correlation to be positive.

An exploratory data analysis (EDA) can be found in the `eda/` directory.

Data

The data for this project comes from Elections BC and "[c]ontains information licenced under the Elections BC Open Data Licence". The project makes use of the "provincial_voter_participation_by_age_group" (Elections BC 2018a) dataset and the "provincial_voting_results" (Elections BC 2018b) dataset.

The pvp dataset, as the name suggests, includes the number of votes as well as the number of registered voters broken down by election and election district. With this information, we can extrapolate the turnout rate per election district for each election. A summary of the dataset is shown in Table 1.

	character	factor	labelled	haven labelled	numeric	integer	logical	Date
Identify miscoded missing values	×	×	×	×	×	×		×
Identify prefixed and suffixed whitespace	×	×	×	×				
Identify levels with < 6 obs.	×	×	×	×				
Identify case issues	×	×	×	×				
Identify misclassified numeric or integer variables	×	×	×	×				
Identify outliers					×	×		×

Table 1. Summary of provincial voting participation dataset.

The pvr dataset contains the number of votes for each candidate and their respective party broken down again by election and election district. From this, we can determine how competitive a race was by calculating the difference in votes between the top two candidates. A summary of the dataset is shown in Table 2.

Identify miscoded missing values	×	×	×	×	×	×		×
Identify prefixed and suffixed whitespace	×	×	×	×				
Identify levels with < 6 obs.	×	×	×	×				
Identify case issues	×	×	×	×				
Identify misclassified numeric or integer variables	×	×	×	×				
Identify outliers					×	×		×

Table 2. Summary of provincial voting results dataset.

Analysis

In order to use the `cor.test()` we need to satisfy ourselves that the assumptions of `cor.test()` are sufficiently met. The first condition of `cor.test()` is the normality of two variables. We check the normality using Q-Q plots (quantile-quantile plots) in Figure 1. These plots show that the normality assumption is reasonable. The second condition is the linearity of covariation which can be examined by looking at the scatter plot of two variables (Figure 2). Since a visual inspection of the scatter plot does not seem to suggest any non-linear pattern, we consider this condition to be valid as well.

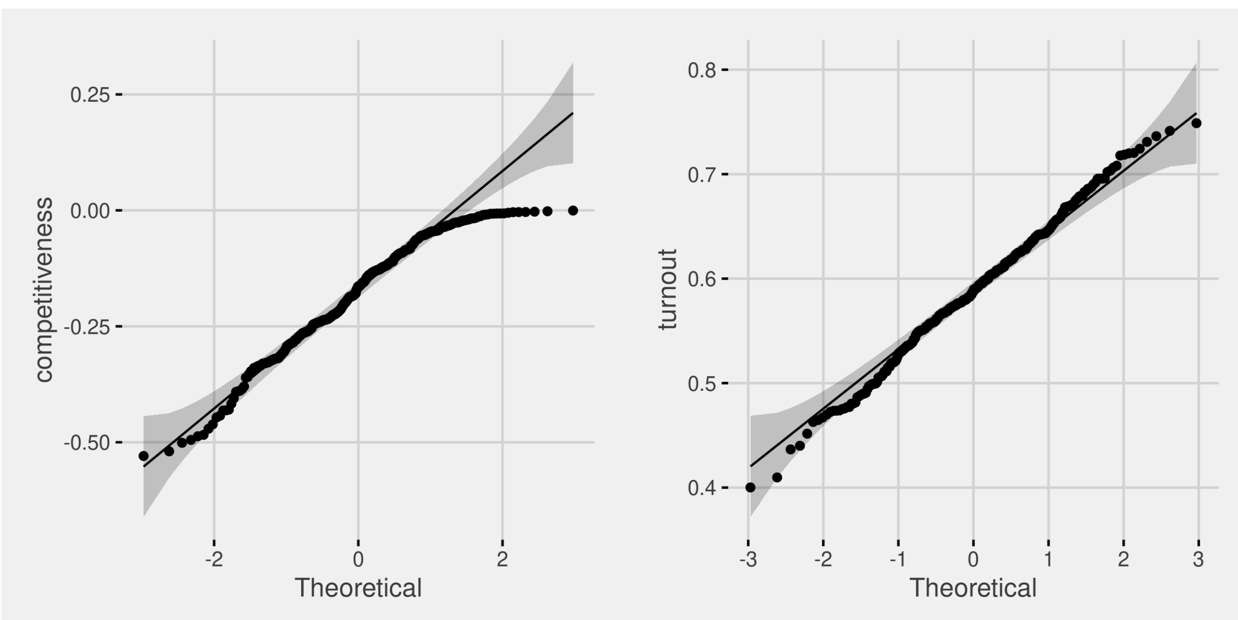
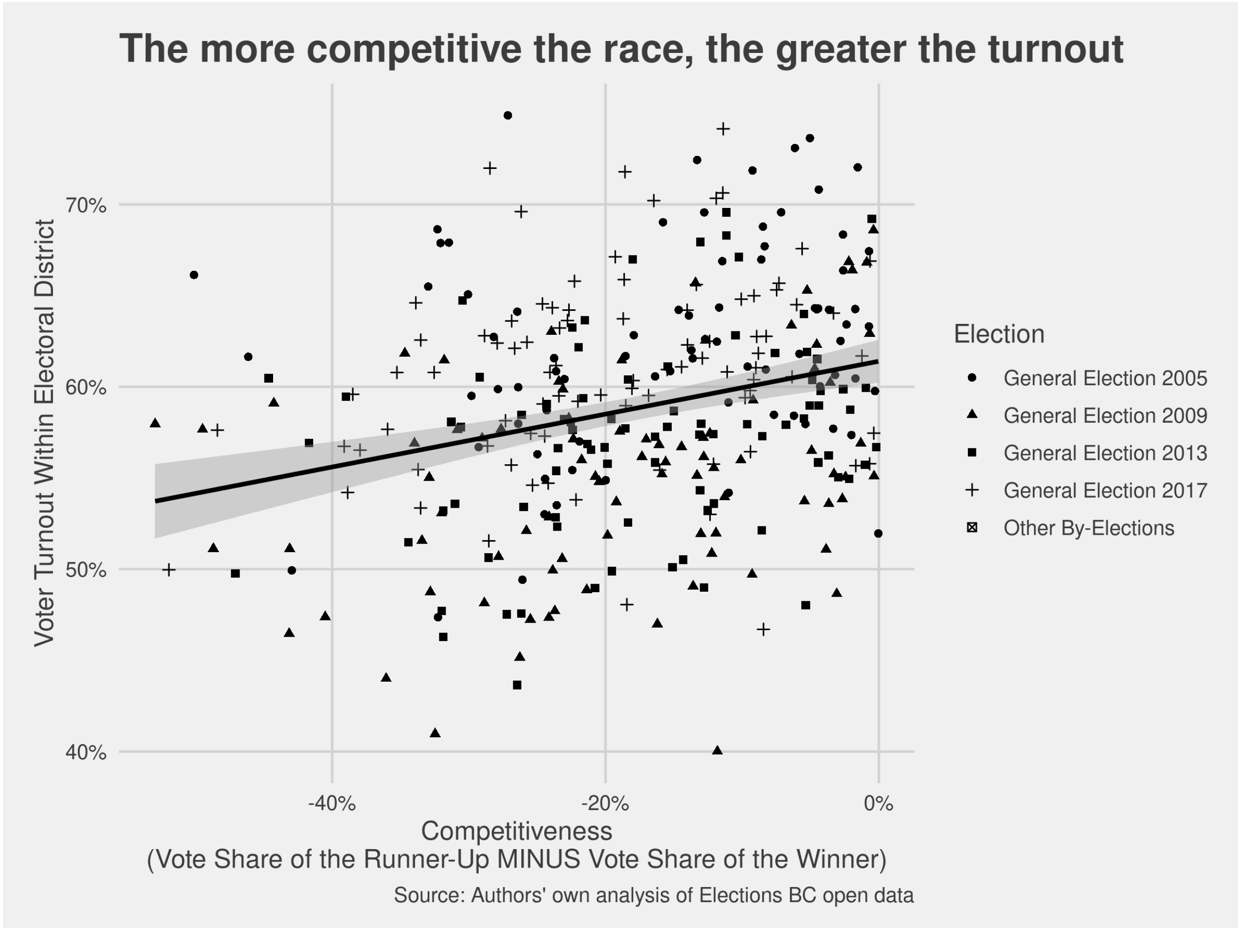


Figure 1. Q-Q plot for competitiveness and turnout.

The scatter plot of competitiveness and turnout is shown in Figure 2. It shows that an electoral district's competitiveness is potentially positively correlated with its voter turnout rate. This matches our expectations. However, in order to understand if their correlation is statistically significant, we will use a two-sided Pearson correlation test via `cor.test()` in R with the following hypotheses:

> **Null Hypothesis:** The correlation coefficient between the voter turnout rate and the race competitiveness is equal to zero.
>
> **Alternative Hypothesis:** The corrrelation coefficient between the voter turnout rate and the race competitiveness is not equal to zero.



\begin{figure}
\caption{Figure 2. A scatter plot displaying competitiveness vs turnout. The grey band is a 95% confidence interval of the regression line slope} \end{figure}

Results and Discussion

Performing the Pearson correlation test in R with `cor.test()` produces the results in Table 3. We observe a positive correlation of 0.27 between the competitiveness of a district and its voter turnout. The final calculated p-value was found to be $p < .001$. This p-value falls below our alpha threshold of 0.05, therefore we reject the null hypothesis and conclude that the linear dependence is statistically significant.

Table 3. Pearson Correlation Test Results

estimate	statistic	p.value	parameter	conf.low	conf.high	method	alternative
0.2727315	5.18075	4e-07	334	0.1707189	0.3689592	Pearson's product-moment correlation	two.sided

While the statistical test above does not make any causal claim, the findings do align with the way many political pundits think about certain causal relationships in elections. Namely, the common thinking is that rivaling political parties, informed by pre-election polls, invest more time and money in campaigning and "getting out the vote" in districts they think might swing the election. This behaviour is likely a product of our "first-past-the-post" system, in which the winner takes all. An interesting angle of analysis to probe this potential explanation further would be to compare whether this correlation holds in jurisdictions that use proportional representation.

Subsequent analysis could also continue to build out a model explaining the voter turnout through multiple regression. Some key variables explored during the exploratory stages includes marginally predictive variables such as the election year. Inclusion of additional variables – and careful quasi-experimental methods and analysis – could help build this model out to a more useful and actionable model for actors in the political space.

R Packages

This project was carried out using the R programming language (R Core Team 2020). The following packages were used within R to carry out the exploratory data analysis and the final analysis: broom (Robinson, Hayes, and Couch 2020), cowplot (Wilke 2020), dataMaid (Petersen and Ekstrøm 2019), docopt (de Jonge 2020), dplyr (Wickham, François, et al. 2020), GGally (Schloerke et al. 2020), ggpubr (Kassambara 2020), ggthemes (Arnold 2019), here (Müller 2020), httr (Wickham 2020a), janitor (Firke 2020), knitr (Xie 2020), stringr (Wickham 2019), testthat (Wickham 2011), tidyr (Wickham 2020b), and tidyverse (Wickham, Averick, et al. 2019).

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