Vote Your Own Pocketbooks, Pocketbooks Relative to Other Pocketbooks, or For or Against Trump: An Analysis of Democratic Two-Party Vote Share Regression Equations - Election Prediction Competition

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Voters vote on the expectation of their economic well-being in the future. I test the hypothesis of a negative Trump residual, in which the years Trump ran would result in worse performance for the Republican vote share. I demonstrate that when Trump runs, on average, the Democratic two-party vote tends to increase by 5.59 percent and that (with 85 percent confidence) the democratic two-party vote share will be around 50-58 percent, indicating a Democratic majority two-party vote in the upcoming 2024 election. My model assumes third party vote share is split equally among Democrats and Republicans. There was about a 2 percent third party vote share, so I assume a 1 percent loss in vote share from each party − thus, my predicted Democratic vote share is 53.14551 and predicted Republican Vote share is 44.85449. I assume this national prediction will be a good proxy for swing states, and I will follow historical results for non-swing states. I also test both hypothesizes, via the Gini coefficient, that 1) a reduction in inequality will increase the incumbent two-party vote share and 2) a reduction in inequality will increase the Democratic two-party vote share. Both changes in the Gini coefficient are statistically insignificant, but in terms of magnitude, inequality reduction tends to have a greater impact on Democratic vote share rather than incumbent vote share. Finally, I run a "horse race" between the WAR and Gini variable (as both could explain voting behavior the 1930-1940s) and find that the WAR variable holds more explanatory power. This paper provides a new perspective testing the combined and individual effects of Trump running and income inequality to determine Democratic two-party vote share.

1. Introduction

When examining why people vote the way they do, a potential theory is that people “vote their pocketbooks” – swing voters predict their financial well-being between candidates and vote for the candidate under whom the voters expect to be in a better financial state. An assumption is that recent economic performance would influence a voter’s expectation of their well-being in the future. Therefore, voters would vote for the incumbent party of the economy is doing well and would vote for the opposition party when the economy is doing poorly (Fair 2011).

There are several factors we could examine to determine if an economy is good or bad − growth rate, inflation, past growth rates/ good news quarters. Furthermore, there are noneconomic factors which may effect voting behavior as well − reelection and duration of the incumbent party, for instance.

When people “vote their pocketbooks,” their pocketbooks relative to other pocketbooks may be of importance. In other words, income inequality may influence the two-party vote share. Through the Gini coefficient, this paper examines two theories: 1) a reduction in inequality will increase the incumbent two-party vote share 2) a reduction in inequality will increase the Democratic two-party vote share. The idea is that a reduction in inequality can be seen as a success of the incumbent party or the success of the Democratic party (due to perceived alignment with Democratic party polices, such as a more progressive tax structure).

Within the past two elections, 2016 and 2020, the Democrats were expected to lose the popular vote, but actually won a majority of the two-party vote, yielding around a 4% error in favor of the Democrats. Besides economic factors, another factor effecting the Democratic vote-share is the presence of Trump, hurting the Republican vote-share and creating a "negative Trump residual."

This paper then combines the **"vote their pocketbooks," "vote their pocketbooks relative to other pocketbooks,"** and the **"vote for or against Trump"** theories together to explain the Democratic two-party vote share.

2. Literature Review

In 1971, Kramer determined that votes are influenced by the economic events during the year of the election. Then, in June 1971, Orley Ashenfelter combined Kramer's economic equation with Fair's prediction of 1972 growth rate of real output. Further development includes Stigler (1973), hypothesizing that well-informed voters look back more than a year and Dwons (1957). Fair then combines all of these hypothesized theories to model the idea that voters interpret previous economic performances of both the Democratic and Republican party and vote for the party with the highest future expected utility. Fair (1978) determines that voters will only evaluate the economic performance of the current political party in power and that voters only look back about a year as the most important economic variable is the growth rate of real per capita output during the year of the election.

Fair then updated the voting equation roughly after each election (1982, 1988, 1990, 1996a, 1998, 2002a, 2006, 2010, 2014, 2018, 2022). When looking at the results of the previous two elections, Democrats were expected to lose the popular vote, but actually won a majority of the two-party vote – I suspect that the presence of Trump running has a negative impact on the Republican party vote share. Political scientists have asserted that Trump is an "unprecedented figure," breaking past decorum and previous practices of presidential behavior Bernhard (2019). Perhaps the negative residual is based on economics, particular in inequality: Doran (2020) finds that Trump's foreign trade sanctions raises concerns on economic insecurity and finds evidence that an increase in the percent an economically insecure population tends to be associated with a significantly worse performance for the Republican candidate.

A way to measure inequality is through an examination of the population living above a certain economic threshold. Doran (2020) finds that districts that have greater proportion of the population living above 150% of the poverty line have a statistically more significant positive changes in the percent voting Republican. Another way to measure inequality is through the Gini Coefficient, which summarizes the dispersion of income across the **entire** income distribution. This paper provides a new perspective testing the combined and individual effects of Trump running and income inequality via the Gini coefficient to determine Democratic two-party vote share.

3. Strategy Replication

3.1 Methodology

To replicate the strategy, data was taken from (https://fairmodel.econ.yale.edu/vote2020/atbl1.txt). The strategy replication will focus on the Democratic share of the two-party presidential vote Vp, and a table of variables and definitions are found below:

3.1a Table of Variables

Table 1: Variables

Variable	Definition
Vp	Democratic share of the two-party presidential vote
Vc	Democratic share of the two-party on-term House vote
I	1 if there is a Democratic presidential incumbent, -1 if there is a Republican presidential incumbent
DPER	1 if a Democratic presidential incumbent is running again, -1 if Republican, and 0 otherwise
DUR	0 if either party has been in the White House for one term, 1 [-1] if the Democratic [Rep.] in the White House for two consecutive terms, and so on
WAR	1 for the elections of 1918, 1920, 1942, 1944, 1946, and 1948, and 0 otherwise
G	Growth rate of real per capita GDP in the first three quarters of the on-term election year
P	Absolute value of the growth rate of the GDP deflator in the first 15 quarters of the administration
Z	Number of quarters in the first 15 quarters of the administration in which real per capita GDP growth > 3.2%
TRUMP	1 if Trump is the running (as the official Republican nominee), and 0 otherwise
GINI	Gini coefficient 4 years before the election minus the Gini coefficient on the year of the election, in Percentage Form

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```

3.2 Results

```
##
## Call:
## lm(formula = VP ~ G:I + P:I + Z:I + DPER + DUR + I + WAR, data = datasetthrough1960)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.0619 -2.0212  0.2674  1.3178  5.4441
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  48.2245     0.6586  73.222  < 2e-16 ***
## DPER          2.1070     1.5767   1.336  0.19722
## DUR          -3.4500     1.3871  -2.487  0.02233 *
## I            -0.8506     2.2680  -0.375  0.71177
## WAR           3.9034     2.7740   1.407  0.17554
## G:I           0.7078     0.1287   5.500 2.64e-05 ***
## I:P          -0.6056     0.3230  -1.875  0.07627 .
## I:Z           0.8654     0.2630   3.291  0.00385 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.01 on 19 degrees of freedom
## Multiple R-squared:  0.8494, Adjusted R-squared:  0.7939
## F-statistic:  15.3 on 7 and 19 DF,  p-value: 1.368e-06
```

The results are now replicated to match the Table 2 of Fair's Presidential and Congressional Vote-Share

Equations, updated on November 2022 (https://fairmodel.econ.yale.edu/RAYFAIR/PDF/2022d.PDF) (Fair 2022).

4 Trump Residual Model

Donald Trump officially ran for president four times in 2000, 2016, 2020, and now in 2024. However, let's only designate Trump's run for president in the years Trump was the official Republican nominee, 2016 and 2020, as he would only be a serious contender to take away the democratic party share of the two-party presidential vote in these instances. A table of the new dataset with the new Trump column is omitted for brevity.

```
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##
## Call:
## lm(formula = VP ~ G:I + P:I + Z:I + DPER + DUR + I + WAR + TRUMP,
##     data = datasetthrough1960_trump)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.6453 -1.2227  0.0765  1.0095  5.3885
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  47.7055     0.6025  79.185  < 2e-16 ***
## DPER          2.8242     1.3924   2.028 0.057589 .
## DUR          -3.8577     1.2119  -3.183 0.005150 **
## I            -1.0435     1.9674  -0.530 0.602308
## WAR           4.5859     2.4180   1.897 0.074052 .
## TRUMP         5.5947     2.0731   2.699 0.014693 *
## G:I           0.6627     0.1128   5.875 1.46e-05 ***
## I:P          -0.7174     0.2831  -2.534 0.020767 *
## I:Z           0.9314     0.2293   4.062 0.000732 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.61 on 18 degrees of freedom
## Multiple R-squared:  0.8927, Adjusted R-squared:  0.8451
## F-statistic: 18.73 on 8 and 18 DF,  p-value: 3.047e-07
```

The t-score for the is TRUMP residual is $2.699 > 2$, and the p-value is 0.015 (less than 0.05), which are both significant. The coefficient of 5.59 on the TRUMP variable indicates that when Trump runs, on average, the democratic two-party vote tends to increase by 5.59 percent.

Potential pitfalls include data mining, as I am purposely adding in the Trump indicator random variable to help explain the 2016 and 2020 elections. In 2016, the Democrats were expected to lose the popular vote with 45.7% of the two-party vote, but actually received 51.2% of the two-party vote, and in 2020, the Democrats were expected to lose with 48.8% of the two-party vote, but actually received 52.2% of the two-party vote. The presence of Trump lead to worse republican results (regarding the percent of the two party vote) and better democratic results that expected – possible reasons include the fact that Trump is a polarizing figure, leading to stronger Democratic vote turnout in election polls or leading to fewer Republican voters.

To test the robustness, I will examine if there is collinearity between the Trump variable and other variables, such as $G \cdot I$ for instance. After introducing the Trump variable, the $G \cdot I$ coefficient changes from 0.708 to 0.6627, a standard error of 0.1287 to 0.1128, and a t-value of 5.5 to 5.88, which are both significant. These changes are minor and even favor the model to be more accurate. The DPER variable now becomes even more statistically significant with a t value increase from 1.336 to 2.028, and the $P \cdot I$ variable becomes statistically significant with a t value of -1.875 to -2.534, which is greater than 2 (in magnitude).

An inclusion of the Trump variable likely increased the accuracy of the DPER variable (incumbency effect) as there could be multicollinearity between DPER and TRUMP – DPER could have been capturing the effect of Trump (especially in 2020, when DPER = -1) and the addition of the TRUMP variable filters out Trump's effect from DPER, allowing DPER to accuracy reflect incumbency. An inclusion of the Trump variable likely increased the accuracy of $P \cdot I$ variable (inflation) as the model can isolate the impact of inflation – Trump's actions could have confounded with inflation potentially due to his initiatives with the **Trade War with China**, which could have affected voter inflation expectations even through actual inflation remained relatively stable. Separating both variables helps us isolate the impact on either Trump or Inflation. Finally, Adjusted R^2 increases from 0.7939 to 0.8451, as the model now can better explain the variation in democratic two-party vote share, and the residual standard error decreases from 3.01 to 2.61.

Let's now predict the 2024 election with this Trump residual, which is equal to 1 since Trump is running. The latest estimates of G, P, and Z are used, which should be relatively similar to election day numbers, but not exact since the election will occur approximately 1 month from now on November 5, 2024.

Let's take economic forecasts from April 25, 2024, with G = 2.23, P = 4.62, and Z = 4, which are the latest forecasts on Ray Fair's website.

```
##        fit      lwr      upr
## 1 54.14551 50.48891 57.80211
```

The predicted democratic two-party vote share is 54.14551 and we are 85% confident that the democratic two-party vote share will be ~50-58%, indicating a Democratic majority two-party vote in the upcoming 2024 election. My model assumes third party vote share is split equally among Democrats and Republicans. There was about a 2% third party vote share, so I assume a 1% loss in vote share from each party – thus, my predicted Democratic vote share is 53.14551 and predicted Republican Vote share is 44.85449. Without the Trump residual, Fair's regression equation predicts a democratic vote share of 51.72%.

5 Adding Income Inequality

When predicting democratic two-party vote share, I will examine the effects of income inequality in addition to the effects of Trump running.

The Gini coefficient data is taken from the World Inequality Database, based on a PPP (Purchasing Power Parity) converted pre-tax national income. The World Inequality Database calculates the Gini coefficient annually from 1913 to 2022, covering our election years of interest from 1916 onwards (except for the upcoming 2024 election). I assume that inequality is a long-run variable as policies often take several years to implement; therefore, this model takes the inequality change over the last 4 years before the election.

To measure the change in inequality, it is important to note that a higher Gini coefficient indicates greater inequality. Over the span of 4 years, I take the Gini coefficient 4 years before the election and subtract the Gini coefficient on the year of the election. This ensures that a decrease in the Gini coefficient yields a positive value. As a side note, for the election of 1916, I subtract the Gini coefficient in 1913 from 1916, and for the predicted 2024 election, I assume the same Gini coefficient in 2024 as in 2022, make an educated guess due to a lack of data at the endpoints.

To test the first theory that a reduction in inequality will increase the incumbent two-party vote share, I will add the multiplication of the Gini variable and I to the regression equation, as a reduction in inequality (positive number) will improve the incumbency. To test the theory that a reduction in inequality will increase the Democratic two-party vote share. I will only add the Gini variable to the regression equation.

I will now test the first theory:

```
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##
## Call:
## lm(formula = VP ~ G:I + P:I + Z:I + DPER + DUR + I + WAR + TRUMP +
##     GINI:I, data = datasetthrough1960_trump)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.6381 -1.2215  0.0778  1.0135  5.3811
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 47.702082   0.626983  76.082  < 2e-16 ***
## DPER         2.820087   1.437224   1.962  0.06633 .
## DUR         -3.866631   1.270578  -3.043  0.00735 **
## I           -1.024344   2.091275  -0.490  0.63052
## WAR          4.561119   2.578734   1.769  0.09487 .
## TRUMP        5.588998   2.138731   2.613  0.01818 *
## G:I          0.662029   0.117654   5.627 3.02e-05 ***
## I:P         -0.718939   0.294222  -2.444  0.02575 *
## I:Z          0.931092   0.236050   3.944  0.00105 **
## I:GINI       0.007659   0.209327   0.037  0.97124
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.685 on 17 degrees of freedom
## Multiple R-squared:  0.8928, Adjusted R-squared:  0.836
## F-statistic: 15.72 on 9 and 17 DF,  p-value: 1.39e-06
```

The coefficient of GINI $\cdot$ I is 0.007659, which indicates that a decrease in inequality (1 percent in the Gini coefficient) will increase the incumbent vote share by 0.766 percent, which is not a large percentage change. Furthermore, the t-value for the GINI coefficient is 0.037, which is not significant (<2). In comparison to regression equation number 2 (which only adds the TRUMP variable), the DUR, TRUMP, G $\cdot$ I, P $\cdot$ I, and Z $\cdot$ I continue to remain significant with a t-value magnitude above 2, but the DPER variable t-score drops from 2.028 to 1.962

I will now test the second theory:

```
## Warning: NAs introduced by coercion

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##
## Call:
## lm(formula = VP ~ G:I + P:I + Z:I + DPER + DUR + I + WAR + TRUMP +
```

```
##     GINI, data = datasetthrough1960_trump)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.5982 -1.2307  0.0864  0.9806  5.3693
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 47.72711    0.63208  75.508  < 2e-16 ***
## DPER         2.83249    1.43235   1.978  0.06443 .
## DUR         -3.88370    1.25519  -3.094  0.00659 **
## I           -1.02088    2.02703  -0.504  0.62098
## WAR          4.45938    2.59342   1.719  0.10368
## TRUMP        5.66359    2.16903   2.611  0.01826 *
## GINI         0.03616    0.21112   0.171  0.86602
## G:I          0.65877    0.11827   5.570 3.39e-05 ***
## I:P         -0.71853    0.29111  -2.468  0.02448 *
## I:Z          0.92693    0.23715   3.909  0.00113 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.683 on 17 degrees of freedom
## Multiple R-squared:  0.8929, Adjusted R-squared:  0.8363
## F-statistic: 15.75 on 9 and 17 DF,  p-value: 1.372e-06
```

The coefficient of GINI is 0.03616, which indicates that a decrease in inequality (1 percent in the Gini coefficient) will increase the Democratic vote share by 3.6 percent. **In terms of magnitude, this second theory has a greater impact on the vote-share (3.6 percent vs. 0.77 percent), potentially indicating that inequality reduction tends to have a greater impact on Democratic vote share rather than incumbent vote share. However, the t-value for the GINI coefficient is 0.171, which is not significant (<2), so this second theory is not statistically significant either.** In comparison to regression equation number 2 (which only adds the TRUMP variable), the DUR, TRUMP, $G \cdot I$, $P \cdot I$, and $Z \cdot I$ continue to remain significant with a t-value magnitude above 2, but the DPER variable t-score drops from 2.028 to 1.978, which is still close to 2.

A potential reason for the ineffectiveness of the GINI coefficient is due lack of large and consistent changes throughout each President's term, which would generally be between 4-8 years.

```
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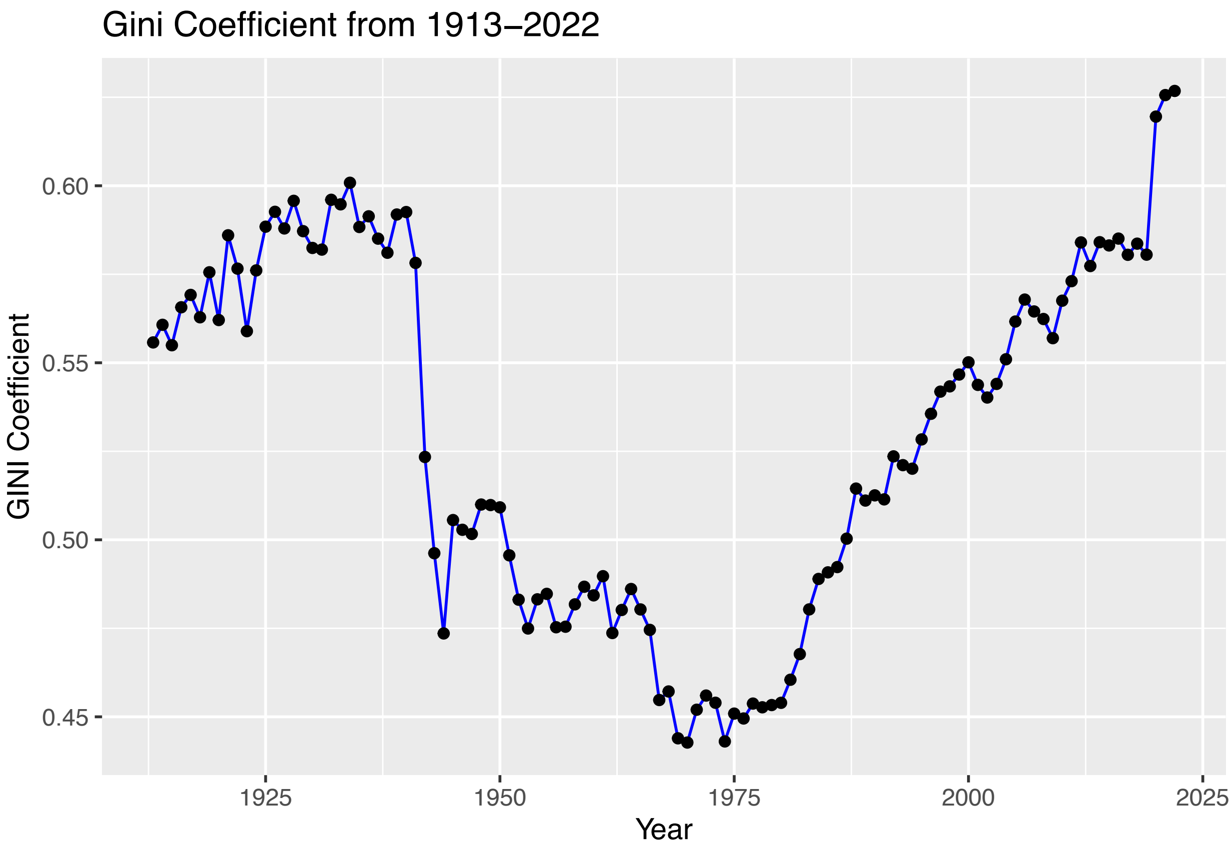
```



Examples of important time periods include 1940 to 1944, in which the Gini coefficient dropped from 0.59 to 0.47, the largest drop over a 4-year time period in the data. During this time frame, Franklin Delano Roosevelt served as president from 1933 to 1945 as a Democrat (although interestingly, FDR was a member of the Harvard Republican Club). FDR enacted numerous policies to reduce economic inequality, including the New Deal, which promoted public work projects and financial reforms, helping the US escape the Great Depression.

In an attempt to improve Fair's model, let's examine the WAR variable, which has a t-statistic of 1.407, below 2. The WAR variable helps explain 1918, 1920, 1942, 1944, 1946, and 1948, which also overlaps with this drop in the GINI coefficient during FDR's presidency from 1933 to 1945. I will now test the hypothesis that the Gini Coefficient could potentially dominate the WAR variable when explaining the democratic two party vote share (especially during the 1930s and 1940s) – let's run a "horse race."

```
##
## Call:
## lm(formula = VP ~ G:I + P:I + Z:I + DPER + DUR + I + WAR + TRUMP,
##     data = datasetthrough1960_trump)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.6453 -1.2227  0.0765  1.0095  5.3885
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  47.7055     0.6025  79.185  < 2e-16 ***
## DPER          2.8242     1.3924   2.028 0.057589 .
## DUR          -3.8577     1.2119  -3.183 0.005150 **
## I            -1.0435     1.9674  -0.530 0.602308
## WAR           4.5859     2.4180   1.897 0.074052 .
```

```
## TRUMP         5.5947     2.0731   2.699 0.014693 *
## G:I           0.6627     0.1128   5.875 1.46e-05 ***
## I:P          -0.7174     0.2831  -2.534 0.020767 *
## I:Z           0.9314     0.2293   4.062 0.000732 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.61 on 18 degrees of freedom
## Multiple R-squared:  0.8927, Adjusted R-squared:  0.8451
## F-statistic: 18.73 on 8 and 18 DF,  p-value: 3.047e-07
```

```
##
## Call:
## lm(formula = VP ~ G:I + P:I + Z:I + DPER + DUR + I + TRUMP +
##     GINI:I, data = datasetthrough1960_trump)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.8664 -1.4958 -0.1780  0.6829  6.3486
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 47.98977    0.64032  74.947  < 2e-16 ***
## DPER         3.42217    1.47658   2.318  0.03245 *
## DUR         -3.17924    1.27921  -2.485  0.02300 *
## I            0.01681    2.12205   0.008  0.99377
## TRUMP        5.13628    2.24539   2.287  0.03449 *
## G:I          0.62990    0.12292   5.124  7.1e-05 ***
## I:P         -0.87045    0.29765  -2.924  0.00906 **
## I:Z          0.73969    0.22184   3.334  0.00369 **
## I:GINI       0.10500    0.21357   0.492  0.62892
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.84 on 18 degrees of freedom
## Multiple R-squared:  0.873,  Adjusted R-squared:  0.8166
## F-statistic: 15.47 on 8 and 18 DF,  p-value: 1.312e-06
```

```
##
## Call:
## lm(formula = VP ~ G:I + P:I + Z:I + DPER + DUR + I + TRUMP +
##     GINI, data = datasetthrough1960_trump)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -4.105 -1.502 -0.150  0.910  6.340
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  48.1087     0.6232  77.197  < 2e-16 ***
## DPER          3.4881     1.4538   2.399  0.02746 *
## DUR          -3.1853     1.2505  -2.547  0.02022 *
## I            -0.1868     2.0723  -0.090  0.92918
## TRUMP         5.4933     2.2815   2.408  0.02699 *
## GINI          0.1396     0.2131   0.655  0.52075
```

```
## G:I            0.6250     0.1228   5.090 7.65e-05 ***
## I:P           -0.8493     0.2959  -2.870  0.01017 *
## I:Z            0.7329     0.2196   3.337  0.00367 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.825 on 18 degrees of freedom
## Multiple R-squared:  0.8743, Adjusted R-squared:  0.8185
## F-statistic: 15.65 on 8 and 18 DF,  p-value: 1.202e-06
```

In the 5th regression equation, VP ~ G:I + P:I + Z:I + DPER + DUR + I + WAR + TRUMP, the War coefficient has a t-value of 1.897 and a coefficient estimate of 4.5859. The coefficient is close to being statistically signifncat. In the 6th and 7th regression equations, I swapped out the War coefficient for the I:GINI and GINI coefficient, respectively, yielding t-values of 0.492 and 0.655. Although these t-statistics for only the GINI coefficient are greater than the t-statistics for the regression equations with both the WAR and GINI variables, they both still fall below 2, so I have low confindence that the GINI coefficient can serve as a predictor for the democratic two party vote-share. Therefore, the WAR coefficient still wins this horse race.

Since the GINI coefficient theories are not statistically significant, I will not incorporating the coefficient to predict the 2024 election results.

7 Conclusion

When examining the theory that voters **"vote their pocketbooks," "vote their pocketbooks relative to other pocketbooks,"** and the **"vote for or against Trump"**, it seems as if "voting their pocketbooks" and "voting against Trump" together can help explain the Democratic two-party vote share. The WAR variable (indicator random variable 1 = War, 0 = No War) "beats" my proposed Gini coefficient!

Further studies include Gini coefficient, but instead of over 4 years, potentially 8 years, as the incumbent president can benefit from the work of the previous president. Alternatively, further studies could examine a different measure of inequality such as intergenerational mobility or even educational inequality. In addition, due to Trump's polarizing figure (and a statistically significant evidence of a negative Trump residual), it is possible that indifferent voters (which were assumed to be equally distributed between both parties) are now voting for the Democratic party – it could be useful to see how these swing voters changed voting preference during the elections involving Trump compared to other elections. Until then, we will see how this Presidential model holds on November 5th!

References

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