The Effect of Economic Events on Votes for the President

Resource Economics 312

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Abstract

The Presidential Equation is a logistic probability model created by Yale University Professor Ray C. Fair to estimate the Democratic share of the two party votes in any given U.S. presidential election. Fair incorporates both economic and political variables to predict which party will gain the majority of votes. This paper recreates and analyzes the significance of Fair's popular election model. We then provided a forecast for the 2020 presidential election. We found Fair's model to hold strong prediction power, providing accurate foresight for every election from 1916 to today. However, the significance of some variables used in his predictions is quite low, leading to questions on how the model remains accurate.

1 Introduction

The "Presidential Equation" is a logistic probability model created by Yale University Professor Ray C. Fair to explain the Democratic share of votes in any given U.S. presidential election. Fair's model takes into account economic and social deterministic factors that influence voters' decisions. This paper will recreate Fair's equation and use it to develop a forecast for the 2020 presidential election given variable economic conditions. This paper will also briefly compare the Fair model to other presidential forecasting models.

2 Literature Review

The Fair (1978) paper was originally published to create a model broad enough where the prominent voting theories of the time could be tested, and to allow testing of these theories against each other. The three main theorists Fair cites in his 1978 paper are Anthony Downs (1957), Gerald H. Kramer (1971), and George J. Stigler (1973).

2.1 Anthony Downs

Anthony Downs (1957) establishes a disconnect between voter desires and government desires. In a perfectly informed democracy, every voter should vote for a government that will maximize social welfare, and the government that gets elected should do just that. Realistically, Downs argues, voters and political representatives do not have complete information, resulting in voting patterns that maximize private economic welfare and a government whose goal is to attain "the income, power, and prestige that come with office" (Downs 1957). Fair's proposed relationship between private economic welfare and voting probability was based on the axioms brought forth by Downs.

2.2 Gerald H. Kramer

Gerald Kramer (1971), when he began studying econometrics, was interested the question of how voting behavior was influenced by macroeconomic events. Primarily, he focused on votes for the House of Representatives and Congress. Kramer found that most of the variance in his predictive model was dependent on the change of personal income in the short term. Other variables such as coattails, unemployment, and inflation did not have significant effects. George Stigler (1973) found an error in Kramer's data, and when the experiment was rerun the output showed that inflation has a "modest independent affect" (Rosenthal 2006). This effect is looked at in Fair's modified equation. Kramer also argued in his 1971 paper that the effect of presidential elections is much more influenced by non-economic events (i.e. candidate personality) than the elections of the House and Congress.

2.3 George J. Stigler

George J. Stigler (1973) reviews Kramer's proposed election model and disassembles the significance of Kramer's proposed relationships. Stigler believes voters think about many confounding factors when they vote, not only Kramer's per-capita income belief. He argues that Kramer doesn't account for past experiences of the voter and incorrectly weights recent economic conditions the same as distant conditions (Stigler 1973). Every voter has a different economic past, so grouping all voters together into an average per capita income statistic can lead to erroneous prediction.

At the time of the original paper, the prevailing theory suggested that a voter looked at the current status and previous performance of the parties seeking power and voted for the party that maximized "future utility" (Kramer 1971, Stigler 1973). A primary assumption, under this theory, was that voters are "self-interested and well-informed" (Fair 1978). More so, Kramer (1971) suggests the voter votes for the party if their performance is deemed "satisfactory".

> The standard assumption in [election forecasts] is that voters hold the party that controls the presidency accountable for economic events, rather than, say, the party that controls the Congress (if it is different) or the Board of Governors of the Federal Reserve System (Fair 1978).

Therefore, as theory would suggest, economic events greatly influence the vote for the president in the United States.

3 Data and Methods

3.1 Data

The data are provided by Fair via his website. We gathered values dating from 1916 to 2012, with observations occuring every four years. The data are limited to a 25 complete observations. With such a small dataset, degrees of freedom and potential modeling power is less than ideal. Upon reciept, the data has been cleaned and tidied. There are no missing values for any of the instances recorded. The data are sourced from the U.S. Bureau of Economic Analysis (BEA) website. Population data are taken from the U.S. Department of Commerce (DOC). Ray Fair has compiled much of the available data to eliminate extraneous variables. The data are readily available on his personal website alongside links to previous updates of the model.

3.2 The Fair Model

The data are presented in Table 1. The updated Fair equation per 1992 is as follows:

$$V_t = \alpha_1 + \alpha_2 G_t \times I_t + \alpha_3 P_t \times I_t + \alpha_4 Z_t \times I_t + \alpha_5 DPER_t + \alpha_6 DUR_t + \alpha_7 I_t + \alpha_8 WAR_t + \mu_t$$

Where, α_n remain unknown coefficients to be estimated. I denotes incumbancy. I equals 1 if the current president is Democratic, -1 if Republican, 0 otherwise.[1] A secondary model testing I as a binay variable is

[1] I serves two functions in Fair's model. First, it interacts with each respective coeffecent to flip the sign of economic variables to either increase the chance of Republicans to win (decreasing V_t) or increase the chance of Democrats to win (increasing V_t). Additionally, I holds a coefficient of its own to demonstrate the effect incumbancy has on voters' decisions.

Table 1: Ray Fair Data

Year	actualVP	I	DPER	DUR	WAR	G	P	Z
1916	0.51	1	1	0.00	0	2.23	4.25	3
1920	0.40	1	0	1.00	1	-11.46	0.00	0
1924	0.43	-1	-1	0.00	0	-3.87	5.16	10
1928	0.43	-1	0	-1.00	0	4.62	0.18	7
1932	0.62	-1	-1	-1.25	0	-14.35	6.93	4
1936	0.64	1	1	0.00	0	11.68	2.50	9
1940	0.55	1	1	1.00	0	3.91	0.05	8
1944	0.53	1	1	1.25	1	4.12	0.00	0
1948	0.50	1	1	1.50	1	3.21	0.00	0
1952	0.44	1	0	1.75	0	1.00	2.35	7
1956	0.42	-1	-1	0.00	0	-1.25	1.91	5
1960	0.50	-1	0	-1.00	0	0.67	1.98	5
1964	0.61	1	1	0.00	0	5.03	1.24	9
1968	0.42	1	0	1.00	0	5.04	3.09	7
1972	0.37	-1	-1	0.00	0	5.83	4.81	4
1976	0.50	-1	0	-1.00	0	3.82	7.46	5
1980	0.41	1	1	0.00	0	-3.58	7.80	5
1984	0.41	-1	-1	0.00	0	5.55	5.21	8
1988	0.46	-1	0	-1.00	0	2.40	2.87	5
1992	0.43	-1	-1	-1.25	0	3.04	3.19	3
1996	0.49	1	1	0.00	0	3.31	2.03	4
2000	0.48	1	0	1.00	0	2.03	1.68	7
2004	0.48	-1	-1	0.00	0	2.09	2.14	2
2008	0.53	-1	0	-1.00	0	-1.79	2.75	2
2012	0.51	1	1	0.00	0	1.42	1.47	1

included in the discussion section of this paper. G has been modified to represent the real growth rate of GDP per capita for the last three quarters of the election year. In contrast to G, a "short horizon" variable, P and Z are longer term variables representing the whole term of the administration. P represents the absolute value of the growth rate of the GDP deflator for the first fifteen quarters of the current administration. Z, the "good news variable", is the number of quarters out of the first fifteen of the current administration where the growth rate of real GDP is greater than 3.2 percent. Fair notes in his construction of the model that psychological research dictates that people will remember extreme events more intensely than normal ones; Z tries to capture the "extreme positive growth outcomes" in accordance with this theory. $DPER$ represents the effect of the current president running while they are in office. $DPER$ equals 1 if current president that will run is Democratic, -1 if Republican, and 0 if the current president will not run while in office. DUR is the duration of the party in office (0 if the current ruling party has been in the White House for one term; $1 \times I$ if current party has held office for two terms; $(1 + k) \times I$ for three terms; $(1 + 2k) \times I$ for four terms; and so on, where k is a chosen value of 0.25). WAR is 1 for the election years during and immediately following a U.S. war (1920, 1944 and 1948) and 0 otherwise.

In forecasts calculated prior to 1996, the original GDP data are presented in a Laspeyres index, which tended to overstate the effect of inflation. Following 1996, GDP is calculated using chain-linked volume series. According to Fair, this more accurately represents the effects of production on the vote-share by providing a better index for growth measurement (Fair 1996).

The model above is the most recent iteration of Fair's presidential equation. Table 2 lists the coefficients derived from the data given in this paper. Table 3 below demostrates the prediction power of Fair's model.

Appendix A shows the full regression table for all regressions run with different variable combinations. Appendix B shows a graphical analysis of the predicted outcomes using Fair's model versus the actual results.

Table 2: Ray Fair 1992 Model Coefficients

term	estimate	std.error	statistic	p.value
(Intercept)	0.462	0.007	69.982	0.000
I	-0.023	0.024	-0.938	0.362
DPER	0.045	0.015	2.927	0.009
DUR	-0.027	0.013	-2.033	0.058
WAR	0.050	0.028	1.793	0.091
I:G	0.007	0.001	5.786	0.000
I:P	-0.009	0.003	-2.834	0.011
I:Z	0.008	0.003	3.153	0.006

Table 3: Fair Prediction Compared with Actual Democratic Share of Votes

Year	Fair_Prediction	Actual_Vote_Share	Error
1916	51.682	50.7	0.982
1920	36.148	39.6	3.452
1924	41.737	42.8	1.063
1928	41.244	43.4	2.156
1932	59.149	61.5	2.351
1936	62.226	64.0	1.774
1940	54.983	54.7	0.283
1944	53.778	53.4	0.378
1948	52.319	49.6	2.719
1952	44.710	44.4	0.310
1956	42.906	42.0	0.906
1960	50.087	49.7	0.387
1964	61.203	61.1	0.103
1968	49.425	42.4	7.025
1972	38.209	37.2	1.009
1976	51.049	50.0	1.049
1980	44.842	41.0	3.842
1984	40.877	40.6	0.277
1988	46.168	45.7	0.468
1992	53.621	43.0	10.621
1996	54.737	49.2	5.537
2000	50.262	48.4	1.862
2004	48.767	48.3	0.467
2008	53.689	52.9	0.789
2012	52.010	51.1	0.910
2016	49.000	48.2	0.800

3.3 Model Replication and Adjustments

3.3.1 Multicollinearity

Multicollinearity is a common problem with time series data and indicates a high degree of correlation between two or more independent variables. When multicollinearity is present, standard errors inflate and calculated t-values decrease. With deflated t-values, the probability of a Type II error (failing to reject an incorrect hypothesis) increases. Type II errors remove the possibility for correct inference to be made about coefficients. One method of detecting multicollinearity is calculating Variation Inflation Factors (VIF) using the formula below.

$$VIF_k = \frac{1}{1 - R_k^2}$$

Table 4: Variance Inflation Factors for the Ray Fair Regression Model

regressor	VIF
I	17.787
DPER	4.557
DUR	4.145
WAR	2.481
I:G	1.397
I:P	4.007
I:Z	6.580

The frequently used heuristic for looking at *Variance Inflation Factors* suggests that any *VIF* greater than **10** indicates a problem. The variable I has a rather high *VIF*. However, this can be attributed to it's interaction affects with the other variables in the model.

3.3.2 Heteroskedasticity

Heteroskedasticity occurs when residual values are different across independent variable values. In a homoskedastic model, residuals are of the same magnitude no matter the value of the independent variable. With unequal variances, a model displays incorrect standard errors, which makes inference impossible. To test for heteroskedasticity, we ran a Breusch-Pagan Test (BP Test) at the 0.05 significance level.

$$\chi^2 = n \times R^2 \sim \chi^2_{(N-1)}$$

Table 5: Breusch-Pagan Test for Heteroskedasticity

statistic	p.value	parameter	method
5.712	0.574	7	studentized Breusch-Pagan test

With a calculated p-value of 0.574 for the chi-squared statistic, we fail to reject the null hypothesis of homoskedasticity for the model. The variance is constant throughout all values of our independent variables.

3.3.3 Autocorrelation

Autocorrelation occurs in a model when the disturbances influence each other over time. With autocorrelation present, standard errors for each coefficient are wrong and inference would be incorrect. We utilized the Durbin-Watson test to check for autocorrelation within our data. We used the d statistic as calculated below and testing it against the null hypothesis $d = 2$ at the 0.05 significance level.

$$d = \frac{\sum_{t=2}^{T}(e_t - e_{t-1})^2}{\sum_{t=1}^{T} e_t^2}$$

Table 6: Durbin-Watson Test for Autocorrelation

statistic	p.value	method	alternative
1.684	0.2	Durbin-Watson test	true autocorrelation is greater than 0

The Durbin-Watson test returns a Durbin-Watson statistic that is not statistically less than 2. This indicates a lack of positive autocorrelation. We fail to reject the null hypothesis that true autocorrelation is greater than 0.

3.3.4 Model Specification and Interpretation

A full regression table with all coefficients (Table 12) is available in Appendix A. Specification of the model began with taking all of the available variables and regressing them on the true Democratic share of the vote.

$$V_t = \alpha_1 + \alpha_2 G_t + \alpha_3 P_t + \alpha_4 Z_t + \alpha_5 DPER_t + \alpha_6 DUR_t + \alpha_7 I_t + \alpha_8 WAR_t + \mu_t$$

This first model had an R^2 of 0.348 and a calculated F-statistic of 1.295 on 7 and 17 degrees of freedom. The p-value for this statistic was 0.3107. This did not indicate model significance at the 5 percent level. The effects of the parameters were minimal, and the only parameter that appeared significant was the intercept (which was significant at the 1 percent level). There seemed to be too much variablity resulting from various incumbent conditions.

Next, we hypothesized that the party of the incumbent may affect the economic variables and their contribution to the vote-share. The second model (designated as "Interaction" at the top of Table 12 in Appendix A) interacted the variable I with G, P and Z, while also leaving non-interacted G, P, and Z in the model.

$$V_t = \alpha_1 + \alpha_2 G_t \times I_t + \alpha_3 P_t \times I_t + \alpha_4 Z_t \times I_t + \alpha_5 DPER_t + \alpha_6 DUR_t + \alpha_7 I_t + \alpha_8 WAR_t + \alpha_9 G_t + \alpha_{10} P_t + \alpha_{11} Z_t + \mu_t$$

Our adjusted-R^2 in this model jumped to 0.8155, with a calculated F-statistic of 11.608 on 10 and 14 degrees of freedom. The p-value for this statistic is significant at less than the 1 percent level, indicating that the model is highly significant. In this model, all of the interaction terms are significant at, at least, the 5 percent level. Other significant parameters include the intercept and $DPER$. While removing insignificant variables can introduce specification bias, we wanted to explore Fair's final model. Fair removed redundancy in his model by removing the non-interated G, P, and Z variables.

Fair's final model is below.

$$V_t = \alpha_1 + \alpha_2 G_t \times I_t + \alpha_3 P_t \times I_t + \alpha_4 Z_t \times I_t + \alpha_5 DPER_t + \alpha_6 DUR_t + \alpha_7 I_t + \alpha_8 WAR_t + \mu_t$$

The model above is the model used from 1992 to present by Ray Fair. This model has an adjusted-R^2 of 0.8327, with a calculated F-statistic of 18.06. The p-value for this statistic is $1.021e - 06$, indicating very high significance. Additionally, all of the parameters, except I and WAR have significance at the 5 percent level (unlike WAR, I has significant interaction with other parameters). What happens if we remove the WAR variable?

$$V_t = \alpha_1 + \alpha_2 G_t \times I_t + \alpha_3 P_t \times I_t + \alpha_4 Z_t \times I_t + \alpha_5 DPER_t + \alpha_6 DUR_t + \alpha_7 I_t + \mu_t$$

After removing the WAR variable, the adjusted-R^2 goes down to 0.8121. Many of the parameters become slightly less significant, but none of them have their coefficients significantly altered. See Table 12 for a side-by-side comparison of the values. We ran a Joint F-test to determine whether the WAR variable is significant.

Table 7: Joint F-Test for WAR parameter

res.df	rss	df	sumsq	statistic	p.value
17	0.014	NA	NA	NA	NA
18	0.017	-1	-0.003	3.214	0.091

The results of the Joint F-test indicate failure to reject the null hypothesis that the two models are equivalent. Given the higher adj-R^2 and higher signficance of the individual parameters, our model will continue to utilize the WAR variable.

Thus, we return to Fair's model (Table 12, Column 3):

$$V_t = \alpha_1 + \alpha_2 G_t \times I_t + \alpha_3 P_t \times I_t + \alpha_4 Z_t \times I_t + \alpha_5 DPER_t + \alpha_6 DUR_t + \alpha_7 I_t + \alpha_8 WAR_t + \mu_t$$

By looking at the significant coefficients, were able to analyze the relationship between the independent and dependent variables. First, both positive economic variables (G and Z) positively affected the party in power. When the economy is doing well, voters tend to attribute the success to the current president. Interestingly, the inflation variable, P, negatively affects the party in power. Voters don't enjoy increasing price levels, which is shown explicitly in the model. The last significant coefficient is $DPER$, which indicates if the current incumbent will run again. Since the coefficient is positive, voters tend to vote for the incumbent if they decide to run again.

4 Forecasting

A key adjunct to this paper is a presidential vote forecast. Fair's presidential equation is notoriours for it's accuracy in predicting the outcome of elections. In 2014, Fair constructed a forecast to the 2016 election by setting all non-economic variables to their respective fixed values and placing predictions on economic variables (Fair 2014). The three separate forecasts for a booming, continuous, or sluggish economy provided by Fair indicated a Republican win barring an economic boom. The economic conditions that followed the 2014 paper resembled his "Economic Slowdown" scenario, affirming his preliminary forecast of a Republican winning the election. Fair's forecast is displayed in Table 7 below.

To further Fair's work, this paper will conduct a forecast for the 2020 presidential election. Our predictions are made similar to the predictions Fair made during his 2014 forecast. We make the assumption that his predictions are sound and therefore excluding discussion on those formulations from this paper. The G, P, Z, $DPER$, DUR, and I variables for the 2020 forecast are as follows:

The non-economic variables in all three scenarios are fixed. $I = -1$ (Republican party is in power), $DPER = -1$ (assuming incumbent president will run again), $DUR = 0$ (Republican party has been in power for only one term), and $WAR = 0$. In the "continued economic conditions" scenario, we input the growth rate of per capita GDP (G) as the growth rate experienced at the end of 2017 (2017:3 - 2017:4) at the annual rate. The value of 1.85 comes from data taken from the Federal Reserve Bank of St. Louis (U.S. Bureau of

Economic Analysis 1947a). The absolute value of the GDP deflator (P) was calculated similarly to the per capita GDP growth rate, taking economic data from 2017 (2016:4 - 2017:4) and determining the growth rate of inflation at the annual rate. For the same reason we are excluding discussion of the derivation of G, we do the same for P. It is explained in depth in Fair 2014. The calculated value for P was 2.35 (U.S. Bureau of Economic Analysis 1947b). Typically, foreasting with this model occurs using the first 8 quarters of the current administration, but there have not been 8 quarters yet. Given there haven't been enough "good news" quarters (Z) yet, the data are showing an upward trend in GDP per capita growth rate. With this trend, our estimate of Z for the "continued economic condition" forecast is 4.

The remaining two scenarios have variable values scaled up or down. For example, in our "Large Boom" scenario, G, or growth rate of GDP per capita, is nearly doubled to estimate how the growth rate would act in a booming economy. The three scenarios forecast the Democratic vote count in 2020 based on three different economic conditions. The next step is to run the three separate scenarios through Fair's presidential equation, with the coefficients shown in the first column of Table 2. In Table 8, the results of the forecast are shown. In all three scenarios, the Democratic share of votes is under 50 percent, indicating a high liklihood of a Republican victory in the 2020 election.

Table 8: 2016 Election Forecast

Possible Economic Condition	G	P	Z	Forecast
Roughly Continued 2014 Rate	2.97	2.14	6	0.49
Large Boom	4.00	2.14	8	0.51
Economic Slowdown	1.00	1.50	2	0.44

Table 9: 2020 Election Forecast

Possible Economic Condition	G	P	Z	Forecast
Roughly Continued 2017 Rate	1.62	1.36	4	0.42
Large Boom	3.00	2.14	8	0.39
Economic Slowdown	0.00	1.50	2	0.46

5 Other Presidential Forecasting Models

Fair's model is praised for it's scope and number of variables. As election forecasting models have grown in popularity, some of the emerging models take similiar approaches to Fair. Others, notably Campbell (1992), opt for a much tighter model specification with fewer independent variables to gain similiar accuracy in their estimates.

Other popular general election models (like the polls-plus, polls-only and now-cast from FiveThirtyEight) combine machine learning algorithms with regression analysis to make estimations. These models combine poll results[2] with economic data, and run tens of thouseands of simulations once the models are calibrated to their specifications (Silver 2016). Many of these models are strong in their predictions, but they are less robust at determining the precise effect of each variable on the outcome. Often, a combination of machine learning and classical regression techniques in these models yield the best results.

[2] "The idea behind an election forecast like FiveThirtyEight's is to take polls ('Clinton is ahead by 3 points') and transform them into probabilities ('She has a 70 percent chance of winning')" (Silver 2016).

6 Discussion

The incumbent variable (I) in Fair's model imposes an equality constraint. When interpreting the interaction coefficients in front of G, P, and Z, an assumption is made that the effect of a one unit change in these variables is identical for when I equals 1 or -1. Or, a change in economic conditions has the same effect on voter preference no matter which party is currently in office. The assumption of equal effects can be naive, for the two parties are known to have unequal effects on the economy.

To test the validity of the restriction, we ran Fair's model with the incumbency variable split into two groups: Democrats and Republicans. To satisfy these conditions, we removed I and replaced it with binary variable $DemI$, which equals 1 when a democratic president is in office and 0 when a Republican president is in office. The split allows for two sets of coefficients to be analyzed: one when a Democrat is in office and one when a Republican is in office. Below are the coefficients and Variation Inflation Factors.

$$V_t = \alpha_1 + \alpha_2 G_t DemI_t + \alpha_3 P_t DemI_t + \alpha_4 Z_t DemI_t + \alpha_5 DPER_t + \alpha_6 DUR_t + \alpha_7 DemI_t + \alpha_8 WAR_t + \alpha_9 G_t + \alpha_{10} P_t + \alpha_{11} Z_t + \mu_t$$

Table 10: Split Incumbent Coefficents

term	estimate	std.error	statistic	p.value
(Intercept)	0.494	0.033	14.863	0.000
DemI	-0.041	0.057	-0.722	0.482
DPER	0.047	0.019	2.421	0.030
DUR	-0.028	0.016	-1.714	0.109
WAR	0.035	0.039	0.899	0.384
G	-0.008	0.002	-4.402	0.001
P	0.006	0.005	1.301	0.214
Z	-0.007	0.004	-1.849	0.086
DemI:G	0.014	0.003	5.253	0.000
DemI:P	-0.019	0.007	-2.816	0.014
DemI:Z	0.016	0.006	2.756	0.015

Table 11: Variance Inflation Factors for Split Incumbent

regressor	VIF
DemI	22.100
DPER	6.458
DUR	5.649
WAR	4.438
G	2.583
P	2.883
Z	3.780
DemI:G	2.978
DemI:P	4.349
DemI:Z	10.320

The "Split Incumbent" model brings party-specific insights on the effect economic factors have on voter preferences. The adj-R^2 for Fair's equal effect model is 0.833 (Table 12) compared to our split incumbent model's adj-R^2 value of 0.815 (Table 13). The similar strength of the models show that splitting the incumbent interaction term does not adversely affect the significance of the model.

Our model brings back the G, P, and Z independent variables that Fair removed. In the Split Incumbent model, the coefficients in front of these non-interacted terms indicate the effect of a one unit change in the economic condition has on the democratic share of votes when a Republican is in office. The coefficients are then changed by the interaction term when a Democratic president is in office.

If Fair's model is correct, we are to expect equal but opposite coefficients for when Republicans or Democrats are in office. However, the economic variable P has significantly different effects on voter behavior depending on who is in office. When a Republican is in office, a one percent increase in the absolute value of the growth rate of the GDP deflator increases the Democratic share of the two-party vote by 0.006 percent. When a Democrat is in office, a one percent increase in the absolute value of the growth rate of the GDP deflator decreases the Democratic share by 0.013. With such a significant difference of effects, the Split Incumbent model illuminates the equality constraint within Fair's model.

7 Conclusion

Many traditional journalists conduct revisionist history when talking about the events leading up to an outcome. Data journalism and election forecasting reverse the methods of traditional outlets of political media. Forecasting models circumvent the political hype surrounding election predictions and instead focus on concrete economic and politcal data. Often, correctness is praised higher than model confidence. Regardless of how well specified the model is, an incorrect forecast is still an incorrect forecast. Traditional media does not care if specificiation bias leads to more accurate forecasts — they exclusively care about who will win the Presidency.

Problems often arise in interpretations of these models. These forecasts and model predictions are representations of uncertainty. To the untrained eye, these forecasts can seem more absolute than they are. Using the example of a presidential election, if the model has a point estimate of 52 percent of the votes going towards the Republican nominee there can be a confidence interval that spans a 49 percent outcome to a 55 percent outcome. Both ends of this interval *can be* equally likely. This paper brings a scrutinizing eye to one of the most accurate election equations: the Fair model. By testing for common errors in time series analysis (such as autocorrelation and heteroskedasticity), we explored possible weaknesses in the model's accuracy. Many of our attempts came up fruitless. Our Split Incumbent model showed how interpretation of Fair's coefficients can be skewed. But, the two models showed nearly identical accuracy. Even when run through our gauntlet of specification tests, the Fair model remains robust.

The forecast section of this paper provides insight on how the Fair model can be used to give preliminary estimates for upcoming elections. A key distinction between the forecast and the model is a decrease in confidence. The economic equation Fair uses to generate his steadfast predictions relies on data only available during the current election year. The forecast in this paper generates three separate estimates for three of the variables (G,P, and Z) based on different possible economic scenarios leading up to the 2020 election. It is very possible that none of the exact scenarios pan out in the coming years. In time, the forecast's strength can be tried with actual economic variables and actual election results. Fair's latest forecast in 2014 correctly forecasted a Republican win in 2016 with respect to actual economic conditions. Our 2018 forecast run through Fair's model predictsa Republican win in the 2020 presidential election, no matter the economic scenario.

8 Appendix A — Regression Results

Table 12: Regression Results

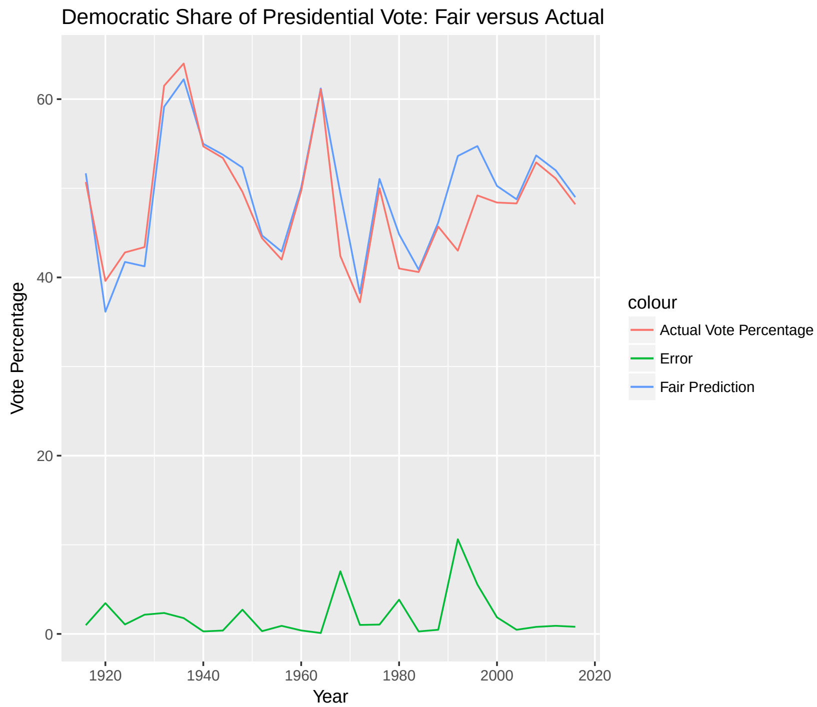
	actualVP			
	Full	Interaction	Fair	No WAR
	(1)	(2)	(3)	(4)
I	0.017	−0.020	−0.023	−0.008
	(0.043)	(0.028)	(0.024)	(0.024)
DPER	0.037	0.047**	0.045***	0.051***
	(0.042)	(0.019)	(0.015)	(0.016)
DUR	−0.042	−0.028	−0.027*	−0.020
	(0.036)	(0.016)	(0.013)	(0.013)
WAR	0.018	0.035	0.050*	
	(0.073)	(0.039)	(0.028)	
G	−0.001	−0.001		
	(0.003)	(0.002)		
P	−0.005	−0.004		
	(0.007)	(0.003)		
Z	0.006	0.000		
	(0.006)	(0.003)		
I:G		0.007***	0.007***	0.007***
		(0.001)	(0.001)	(0.001)
I:P		−0.010**	−0.009**	−0.011***
		(0.003)	(0.003)	(0.003)
I:Z		0.008**	0.008***	0.006**
		(0.003)	(0.003)	(0.002)
Constant	0.467***	0.473***	0.462***	0.466***
	(0.045)	(0.021)	(0.007)	(0.007)
Observations	25	25	25	25
R^2	0.348	0.892	0.881	0.859
Adjusted R^2	0.079	0.815	0.833	0.812
Residual Std. Error	0.067 (df = 17)	0.030 (df = 14)	0.029 (df = 17)	0.030 (df = 18)
F Statistic	1.295 (df = 7; 17)	11.608*** (df = 10; 14)	18.060*** (df = 7; 17)	18.286*** (df = 6; 18)

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 13: Regression Results

	actualVP Split Incumbent
DemI	−0.041
	(0.057)
DPER	0.047**
	(0.019)
DUR	−0.028
	(0.016)
WAR	0.035
	(0.039)
G	−0.008***
	(0.002)
P	0.006
	(0.005)
Z	−0.007*
	(0.004)
DemI:G	0.014***
	(0.003)
DemI:P	−0.019**
	(0.007)
DemI:Z	0.016**
	(0.006)
Constant	0.494***
	(0.033)
Observations	25
R^2	0.892
Adjusted R^2	0.815
Residual Std. Error	0.030 (df = 14)
F Statistic	11.608*** (df = 10; 14)
Notes:	***Significant at the 1 percent level.
	**Significant at the 5 percent level.
	*Significant at the 10 percent level.

9 Appendix B — Graph



10 Technical Documentation

Written using R (R Core Team 2013).

Packages used:

- knitr, Xie (2018)
- MASS, Venables and Ripley (2002)
- xtable, Dahl (2016)
- mosaic, Pruim, Kaplan, and Horton (2017)
- readxl, Wickham and Bryan (2017)
- dplyr, Wickham et al. (2017)
- Stargazer, Hlavac (2018)
- DataExplorer, Cui (2018)
- tidyverse, Wickham (2017)
- randomForest, Liaw and Wiener (2002)
- car, Fox and Weisberg (2011)
- gplot2, Wickham (2009)
- sjPlot, Lüdecke (2018)
- broom, Robinson (2018)
- texreg, Leifeld (2013)
- forecast, Hyndman and Khandakar (2008)
- lmtest, Zeileis and Hothorn (2002)

References

Campbell, James E. 1992. "Forecasting the Presidential Vote in the States." *American Journal of Political Science* 36 (2):386–407. https://doi.org/10.2307/2111483.

Cui, Boxuan. 2018. *DataExplorer: Data Explorer*. https://CRAN.R-project.org/package=DataExplorer.

Dahl, David B. 2016. *Xtable: Export Tables to Latex or Html*. https://CRAN.R-project.org/package=xtable.

Downs, Anthony. 1957. "An Economic Theory of Political Action in a Democracy." *Journal of Political Economy* 65 (2 (Apr., 1957)):135–50. http://www.jstor.org/stable/1827369.

Fair, Ray C. 1978. "The Effect of Economic Events on Votes for President." *The Review of Economics and Statistics* 60 (2):159–73. https://doi.org/10.2307/1924969.

———. 1996. "The Effect of Economic Events on Votes for President: 1992 Update." *Political Behavior* 18 (2):119–39. http://www.jstor.org/stable/586603.

Fox, John, and Sanford Weisberg. 2011. *An R Companion to Applied Regression*. Second. Thousand Oaks CA: Sage. http://socserv.socsci.mcmaster.ca/jfox/Books/Companion.

Hlavac, Marek. 2018. *Stargazer: Well-Formatted Regression and Summary Statistics Tables*. Bratislava, Slovakia: Central European Labour Studies Institute (CELSI). https://CRAN.R-project.org/package=stargazer.

Hyndman, Rob J, and Yeasmin Khandakar. 2008. "Automatic Time Series Forecasting: The Forecast Package for R." *Journal of Statistical Software* 26 (3):1–22. http://www.jstatsoft.org/article/view/v027i03.

Leifeld, Philip. 2013. "texreg: Conversion of Statistical Model Output in R to LaTeX and HTML Tables." *Journal of Statistical Software* 55 (8):1–24. http://www.jstatsoft.org/v55/i08/.

Liaw, Andy, and Matthew Wiener. 2002. "Classification and Regression by randomForest." *R News* 2 (3):18–22. https://CRAN.R-project.org/doc/Rnews/.

Lüdecke, Daniel. 2018. *SjPlot: Data Visualization for Statistics in Social Science*. https://CRAN.R-project.org/package=sjPlot.

Pruim, Randall, Daniel T Kaplan, and Nicholas J Horton. 2017. "The Mosaic Package: Helping Students to 'Think with Data' Using R." *The R Journal* 9 (1):77–102. https://journal.r-project.org/archive/2017/RJ-2017-024/index.html.

R Core Team. 2013. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. http://www.R-project.org/.

Robinson, David. 2018. *Broom: Convert Statistical Analysis Objects into Tidy Data Frames*. https://CRAN.R-project.org/package=broom.

Rosenthal, Howard. 2006. "Gerald H. Kramer. 1971. "Short-Term Fluctuations in U.S. Voting Behavior, 1896-1964." "American Political Science Review" 71 (March): 131-43." *The American Political Science Review* 100 (4):672–74. http://www.jstor.org/stable/27644401.

Silver, Nate. 2016. "A User's Guide to FiveThirtyEight's 2016 General Election Forecast." *FiveThirtyEight*. https://fivethirtyeight.com/features/a-users-guide-to-fivethirtyeights-2016-general-election-forecast/.

Stigler, George J. 1973. "General Economic Conditions and National Elections." *The American Economic Review* 63 (2):160–67. http://www.jstor.org/stable/1817068.

U.S. Bureau of Economic Analysis. 1947a. "FRED Rgdp 1947 - 2018." https://fred.stlouisfed.org/series/A939RX0Q048SBEA.

———. 1947b. "Gross Domestic Product: Implicit Price Deflator." *FRED, Federal Reserve Bank of St. Louis*. https://fred.stlouisfed.org/series/GDPDEF.

Venables, W. N., and B. D. Ripley. 2002. *Modern Applied Statistics with S*. Fourth. New York: Springer. http://www.stats.ox.ac.uk/pub/MASS4.

Wickham, Hadley. 2009. *Ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York. http://ggplot2.org.

———. 2017. *Tidyverse: Easily Install and Load the 'Tidyverse'*. https://CRAN.R-project.org/package=tidyverse.

Wickham, Hadley, and Jennifer Bryan. 2017. *Readxl: Read Excel Files*. https://CRAN.R-project.org/package=readxl.

Wickham, Hadley, Romain Francois, Lionel Henry, and Kirill Müller. 2017. *Dplyr: A Grammar of Data Manipulation*. https://CRAN.R-project.org/package=dplyr.

Xie, Yihui. 2018. *Knitr: A General-Purpose Package for Dynamic Report Generation in R*. https://CRAN.R-project.org/package=knitr.

Zeileis, Achim, and Torsten Hothorn. 2002. "Diagnostic Checking in Regression Relationships." *R News* 2 (3):7–10. https://CRAN.R-project.org/doc/Rnews/.