PREDICTING PRESIDENTIAL ELECTIONS WITH EQUALLY-WEIGHTED REGRESSORS IN FAIR'S EQUATION AND THE FISCAL MODEL[1]

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Abstract

Three-decade old research suggests that although regression coefficients obtained with Ordinary Least Squares (OLS) are optimal for fitting a model to a sample, unless the *N* over which the model was estimated is large, they are generally not very much superior and frequently inferior to equal weights or unit weights for making predictions in a validating sample. Yet, that research has yet to make an impact on presidential elections forecasting, where models are estimated with fewer than 25 elections, and often no more than 15. In this research note, we apply equal weights to generate out-of-sample and one-step ahead predictions in two sets of related presidential elections models, Fair's presidential equation and the fiscal model. We find that most of the time, using equal weights coefficients does improve the forecasting performance of both.

1. Introduction

In a recent paper, Hogarth (2006) revisits three-decade old findings by himself and others showing that although regression coefficients obtained with Ordinary Least Squares (OLS) are optimal for fitting a model to a sample, unless the *N* over which the model was estimated is large, they are generally not superior and often inferior to equal weights or unit weights for making predictions in a validating sample. Yet, that research has yet to make an impact on economics—or, more to the point of this research note, presidential elections forecasting.

Drawing *inter alia* on several of the studies Hogarth surveyed, in this paper we briefly summarize the case for equal weights coefficients in forecasting. Next, we apply equal weights to out-of-sample and one-step-ahead predictions in two related presidential elections models, Fair's equation and the fiscal model. Fair (1978) pioneered forecasting presidential elections with a regression model that relies on "fundamentals" (Nordhaus 2006), not polling data. So does the fiscal model, a recent newcomer to the field of elections forecasting, although it saw light as an explanatory model only a few years after Fair's (Cuzán and Heggen, 1984). In its present version, the fiscal model borrows several of its variables from Fair's, and for that reason has been variously characterized as a "variant" (Nordhaus 2006), "extension" (Jones 2008) or "amended version of Fair's equation" (Campbell and Lewis-Beck 2008). For an earlier comparison on the fitting and forecasting performance of the two, see Cuzán and Bundrick (2005). In this paper, we show that although the results are not all in the same direction, using equal weights coefficients generally improves the forecasting performance of both models.

2. The Case for Equal Weights Coefficients in Predictions

The case for using equal weights regression models in making predictions when the number of observations is small has been made over the last four decades (Schmidt 1971; Dawes and Corrigan 1974; Einhorn and Hogarth 1975; Weiner 1976; Dawes 1979; Armstrong 1985, Chapter 8; Dana and Dawes, 2004). Very summarily, the argument goes as follows. Coefficients calculated with Ordinary Least Squares (OLS) multiple regression procedures are optimal for fitting a model to existing data, i.e., to estimate a "measurement model," but often these same coefficients will not do as well as equal weights in a "forecasting model," one designed to make predictions in a new sample. (The terminology is from Armstrong 1985, 219). This is because a model with "optimal" coefficients uses up degrees of freedom with each additional regressor, is affected by outliers, fits some of the noise in the data, and is sensitive to correlations among the predictors and other violations of assumptions of multiple regression. This shrinkage also occurs in out-of-sample and one-step ahead predictions. Assigning equal weights to all coefficients avoids these problems. Usually, modeling the same data with equal weights coefficients results in a small loss of fit, but this is offset by fewer prediction errors or a smaller mean absolute error when the model is applied to a different sample.

The minimum *N* at which OLS-estimated weights have been found to perform better at prediction has been variously estimated. Claudy (1972) sets N at no less than 200. However, other researchers condition it on the number of predictors in the initial model. For example, Dawes and Corrigan (1974) place it at between 20:1 and 25:1. Still others say that the threshold depends not only on this ratio but on the fit of the initial OLS regression model. Einhorn and Hogarth (1975) suggest a ratio of 10:1 for well-fitting models. This estimate is close to Schmidt's (1971), who found that when predictors are four or fewer and $N \leq 50$, unit weights outperform optimal weights regardless of initial model fit. Considering that presidential elections forecasting models are estimated with fewer than 25 cases and in some cases with no more than 15, and that the number of predictors ranges anywhere from three to seven, resulting in an average ratio of 4:1 (Cuzán and Bundrick 2005a), these estimates are sobering indeed.

The literature suggests several ways for developing equal weights models. Two "families" of methods are most relevant for our purposes. In both, all predictors are so aligned as to have a positive effect on the dependent variable and either raw or normalized scores (with a mean of 0 and a variance of 1) are used for the regressors and/or the dependent variable. In one approach, the unit weight method, all coefficients are assigned a value of 1 (+ and – are used to maintain a positive effect between regressor and dependent variable). In another, equal weights are utilized—with the weights arbitrarily picked by the investigator, drawn at random, or selected with a "restricted" OLS regression procedure in which "all the regression coefficients are restrained to be equal" (Einhorn and Hogarth, 1975, 184).

We experimented with various combinations of each method. Our best results were obtained by normalizing only the regressors, and using an OLS regression procedure to find the best fit under the constraint that the coefficients be equal (but not necessarily one). In this case, “best results” refers to the out-of-sample and one-step-ahead predictions generated by the model across the sample data set, since we don’t have the luxury of taking a validating sample on which to apply and judge the model.

3. Applying Equal Weights to Fair’s Equation and the Fiscal Model

Variable definitions and specifications for Fair’s presidential vote equation, as well as for the fiscal model, are shown in Table 1. In both, the dependent variable is VOTE2, the percent of the two-party vote going to the incumbent, the president or his party’s candidate.

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Table 1 about here

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Fair’s equation consists of seven regressors. The first three are economic: GROWTH, the expected annualized rate of per capita growth through the first three quarters of the election year; GOODNEWS, the number of quarters during the presidential term when GROWTH exceeds 3.2%; and INFLATION, the absolute change in the price level during the presidential term. Also included are four political variables: PERSON, which stands for whether the president himself is a candidate for reelection; his PARTY, Democrat (+1) or Republican (-1); DURATION, a weighted index of the number of consecutive terms the incumbents have controlled the White House; and WAR. Fair adjusts two of his three economic variables, INFLATION and GOODNEWS, assigning a value of 0 in three “war” years (1920, 1944, and 1948). Fair’s expectations are that

GROWTH, GOODNEWS, and PERSON have a positive effect on the vote, and that INFLATION, DURATION, and PARTY have a negative effect. WAR is a control variable.

The fiscal model consists of five regressors. Three are borrowed from Fair's data set: GROWTH, GOODNEWS, and DURATION. However, in the case of GOODNEWS the real values of the variable are restored in the "war" years. Thus, we convert it into ALLNEWS. Also included in the fiscal model is the PARTY of the incumbents, because not only Fair but Alessina and Rosenthal (1995), too, find that historically Republicans have done better than Democrats at the polls. This is purely an empirical control.

The fifth and last factor in the fiscal model, what distinguishes it from every other presidential elections model, is a measure of spending policy: the change in the ratio of federal outlays to GDP between election years (F). Note that this variable tracks relative, not total spending. The federal budget may grow in absolute terms, but fall or remain constant in relation to the economy. In the past, we have measured the change in F with FISCAL, a binary variable constructed with F1 and F2, respectively the first and second derivative of F. If $F1>0$ and $F2\geq0$, this means that in the current term F has increased at the same or faster rate than in the previous administration. In those cases, fiscal policy is labeled "expansionary," and FISCAL is coded +1. On the other hand, if $F1<0$, regardless of the value of F2, this indicates that F has contracted since the last election. Also, if $F1>0$ and $F2<0$, this shows that in the current term F has grown at a slower rate than in the previous term; in other words, its rate of growth has decelerated. Both are considered cases of fiscal cutback, and FISCAL is coded -1. (The case where F1=0 is theoretically possible but does not occur in the data set.) More recently, we have experimented with a simpler measure, FPRIME, also a binary variable which takes the value of 1 is F1 is positive (fiscal policy is "expansive") and -1 if it is negative (fiscal policy is "contractionary"). With either version of the fiscal model, the incumbents are expected to win reelection if fiscal policy contracts, and to lose if it expands. For the theoretical rationale, see Cuzán and Bundrick (2008) and Cuzán, Heggen, and Bundrick (2009). All other variables are hypothesized to behave as in Fair's model.

For the purpose of forecasting, both models are estimated with all elections starting with that of 1916. As shown in Table 2, all three models have a reasonably good fit with the data. In terms of both the Mean Absolute Error (MAE) of the in-sample predictions and the Hit Rate (the percent of correct predictions), the fiscal model with FPRIME performs best. It missed only three elections, all close contests (where 48≤VOTE2≤52), whereas the other two missed at least one election that was nowhere close (1992 or 2008).

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Table 2 about here

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Parenthetically, it may be wondered why we evaluate the models on the Hit Rate as well as the MAE. It seems to us that for some purposes it is more desirable that a model be able to pick the winner ahead of time as opposed to just having the smaller MAE. We submit that, given the choice, those whose overriding interest lies in who will be in the White House, namely the media, lobbyists of all sorts, and foreign governments, prefer a model with the highest percentage of hits over one with the lowest MAE.

As mentioned, we experimented with several equal weights methods for all three models. Here we report only the results obtained from the best-performing method. The coefficients for each of the three models were estimated using OLS regression on normalized regressors, all so aligned as to have a positive effect on VOTE2, with the added constraint of "equal weights," that is, that they all have the same influence on VOTE2. Please see Table 3 for the results. All coefficients are statistically significant and in the hypothesized direction. As expected, compared to their OLS counterparts the equal weights models do not fit the data as well. Across the three models, the R-square is slightly lower and the in-sample prediction MAEs higher. However, in two of the three models (Fair's equation and the fiscal model with FPRIME), the equal weights method yields more hits.

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Table 3 about here

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Next, we compare the performance of the OLS and equal weights variants of these models in out-of-sample forecasting. To do this, all models we re-estimated 24 times, each using *N*-1 elections, sequentially; in turn, each of the 24 models was used to "predict" the election outcome omitted from those over which it was calibrated. The results are shown in Table 4. Across all three cases, equal weights models outperformed their OLS counterparts, incurring smaller MAEs and in two cases more correct predictions. The largest improvement is obtained with Fair's equation, where the number of miscalls is slashed in half. In fact, the number of hits obtained with equal weights is greater than that of the model's *original in-sample* showing using standard OLS: 21 vs. 19.

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Table 4 about here

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Finally, we look at the performance of both sets of models, respectively with optimal and with equal weights, in one-step ahead forecasting. In order to allow enough data to fit the optimal OLS models, the series starts with the 1952 election. We first estimated all six models with the previous nine elections, and used them to predict 1952 results. Next, we re-estimated the models with the 1916-1952 elections, and predicted for 1956. We proceeded in this manner, at every step incorporating one additional election into each model to predict the one immediately following, through 2008. Displayed in Table 5, the results are mixed. In the fiscal models, equal weights outperform optimal weights in the MAE or the Hit Rate. In the case of Fair's equation, equal weights yield a larger MAE (3.1 vs. 2.3), but one more hit.

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Table 5 about here

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As an additional test, we re-estimated all models over the 1880-2008 period. Fair includes data on all his variables for this extended period although, as noted, for forecasting purposes he estimates his equation starting with the 1916 election. The results, not shown for lack of space, are consistent with those obtained over the shorter period. Across all models, the MAE shrinks between

0.70 and 2.0 points with the one-step-ahead method, and around 0.25 points with the out-of-sample method. The Hit Rate rises in Fair's equation with either method, as well as in the fiscal model with FPRIME with the one-step-ahead method; it falls slightly in the latter with the out-of-sample method and in its sister model with FISCAL with the one-step-ahead method. The largest gains are obtained with Fair's model.

4. Conclusion

In this research note we evaluated the idea that equal weights can outperform optimal weights in regression models with a relatively small ratio of observations to predictors, as is the case in three presidential elections forecasting models, Fair's equation and two versions of the fiscal model. We found that in all three models standardizing the predictors and restraining the regression coefficients to be equal, without necessarily taking the value of 1, yields either more in-sample and out-of-sample correct predictions of whether the incumbents will retain the White House, or a smaller absolute error of the prediction of their share of the two-party vote. These results held over two time periods, 1880-2008 and 1916-2008. In one-step ahead forecasting, the results are the same in the fiscal models. In Fair's equation, estimated over the shorter period there is a tradeoff: equal weights scored more hits, but at the cost of a higher error in the predicted vote.

These findings, then, are generally supportive of the three-decade old research by Hogarth and others concerning the value of equal weights for prediction when the *N* over which a model is fitted is small. If the findings with Fair's equation and the fiscal model are representative, there appears to be little or no downside to the equal-weights method in forecasting presidential elections. This is especially the case if one is more interested in predicting the winner than in minimizing the error in the margin of victory. Given that all presidential elections forecasting models are estimated with fewer than 25 observations, and usually no more than 15, it would be interesting to conduct more experiments with equal weights in presidential elections forecasting.

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Table 1. Variable Definitions.

VARIABLE	DEFINITION AND MEASUREMENT
VOTE2	Percent of the two-party vote won by the incumbent party candidate, except that in the 1924 election Fair assigned 23.5 percent of the Lafayette vote to President Coolidge and the rest to the Democratic candidate.
GROWTH	The "growth rate of real per capita GDP in the first three quarters of the election year (annual rate)."
GOODNEWS	The "number of quarters in the first 15 quarters of the administration in which the growth rate of real per capita GDP is greater than 3.2 percent at an annual rate except for 1920, 1944, and 1948, where the values are zero."
ALLNEWS	ALLNEWS=GOODNEWS, except that in 1920, 1944, and 1948, the actual values are entered. We thank Prof. Fair for sharing them with us.
INFLATION	The "absolute value of the growth rate of the GDP deflator in the first 15 quarters of the administration (annual rate) except for 1920, 1944, and 1948, where the values are zero."
PERSON	"*PERSON*=1 if the incumbent president is running for election and 0 otherwise." Note, though that "Ford was not counted as an incumbent running again because he was appointed vice president rather than running on the original ticket."

DURATION	"DURATION 0 if the incumbent party has been in power for one term, 1 if the incumbent party has been in power for two consecutive terms, 1.25 if the incumbent party has been in power for three consecutive terms, 1.50 for four consecutive terms, and so on"
PARTY	PARTY=1 if the Democrats occupy the White House, and PARTY=-1 if the Republicans are the incumbents.
WAR	"WAR=1 for the elections of 1920, 1944, and 1948 and 0 otherwise."
	Fiscal policy: expansionary (1) or cutback (-1):
FISCAL	FISCAL=1 if F1>0 *and* F2≥0 FISCAL=-1 if F1<0 *or* F2<0 FISCAL=0 if F1=0 *and* F2=0 (there is no such case in the data).
FPRIME	FPRIME: expansionary (1) or contractionary (-): FPRIME=1 if F1>1 FPRIME=-1 if F1<1

Note: All quotes are from Fair (2006).

Table 2. Fair's Equation and Two Versions of the Fiscal Model Compared

Dependent Variable: VOTE2 (Incumbent's Share of Two-Party Vote)

t-values in parenthesis (all significant at .05 or less)

In-sample predictions

1916-2008 (*N*=24)

	Model		
	Fair's Equation	Fiscal Model with	
Variable		FISCAL	FPRIME
FISCAL		-2.04 (-3.68)	
FPRIME			-2.17 (-5.20)
DURATION	-3.29 (-2.77)	-3.41 (-3.73)	-4.21 (-5.92)
PARTY	-2.63 (-4.31)	-2.42 (-4.52)	-2.08 (-4.74)
ALLNEWS		0.92 (4.96)	0.94 (6.04)
GOODNEWS	1.11 (4.64)		
GROWTH	0.68 (6.26)	0.66 (6.91)	0.68 (8.49)

INFLATION	-0.64 (-2.26)		
PERSON	3.50 (2.61)		
WAR	5.85 (2.24)		
INTERCEPT	46.80 (19.61)	47.61 (35.31)	48.71 (44.82)
SEE	2.49	2.36	1.98
R^2	0.91	0.91	0.93
Adj. R^2	0.86	0.88	0.92
D.W.	2.65	1.77	1.63
1st order auto-corr.	-0.36	-0.03	0.16
MAE	1.68	1.49	1.32
Largest error (year)	4.18 (1992)	5.3 (2008)	-4.0 (1964)
Elections Missed	1916, 1960, 1968, 1992, 2000	1948, 1976 2008	1948, 1968 1976
Hit Rate	79%	88%	88%

Table 3. Normalized Regressors and Equal Weights Coefficients

Dependent Variable: VOTE2 (Incumbent's Share of Two-Party Vote)

t-values in parentheses; in-sample predictions.

1916-2008 (*N* = 24)

	Model		
	Fair's Equation	Fiscal Model with	
		FISCAL	FPRIME
All Variables	2.49 (9.11)	2.59 (12.12)	2.76 (13.74)
INTERCEPT	52.09 (80.48)	52.09 (102.76)	52.09 (114.02)
SEE	3.17	2.48	2.24
R^2	0.79	0.87	0.896
Adj. R^2	0.78	0.87	0.89
D.W.	2.19	1.35	1.22
1st order auto-corr.	-0.096	-0.196	0.37
MAE	2.21	1.75	1.59
Largest error (year)	8.69 (1920)	6.66 (1980)	-5.55 (1968)
Elections Missed	1988, 1992 2000	1948, 1976 1980, 2008	1948, 1976

Hit Rate	88%	83%	92%

Note: All regressors are statistically significant at 0.01 or better and have the same effect on the VOTE2, only in the direction shown in the OLS models displayed in Table 2.

Table 4. 1 Out-of-sample Diagnostics: Optimal vs. Equal Weights in Fair's Equation and Two Versions of the Fiscal Model 1916-2008 (*N=24*)

Models	MAE	Largest Error (Year)	Hit Rate	Elections Missed
Optimal Weights				
Fair's Equation	2.75	9.83 (1920)	71	1916, 1948, 1960, 1968, 1988, 1992, 2000
Fiscal Model with FISCAL	1.99	6.63 (2008)	83%	1948, 1976, 1980, 2008
Fiscal Model with FPRIME	1.85	-6.32 (1932)	88%	1948, 1968, 1976
Equal Weights				
Fair's Equation	2.55	10.23 (1920)	88%	1988, 1992, 2000
Fiscal Model with FISCAL	1.91	6.96 (1980)	83%	1948, 1976, 1980, 2008
Fiscal Model with FPRIME	1.74	-5.88 (1964)	92%	1948, 1976

Table 5. One-step Ahead Diagnostics: Optimal vs. Equal Weights in Fair's Equation and Two Versions of the Fiscal Model 1916-2008 (*N=24*)

Models	MAE	L.E. (Year)	Hit Rate	Elections Miscalled
Optimal Weights				
Fair's Equation	2.33	-5.28 (1952)	75%	1960, 1976 1992, 2000
Fiscal Model with FISCAL	2.26	6.63 (2008)	75%	1960, 1976 1980, 2008
Fiscal Model with FPRIME	1.92	-5.05 (1964)	75%	1948, 1960, 1968, 1976
Equal Weights				
Fair's Equation	3.09	-8.39 (1952)	81%	1988, 1992, 2000
Fiscal Model with FISCAL	2.22	7.56 (1980)	75%	1948, 1976 1980, 2008
Fiscal Model with FPRIME	1.81	-6.01 (1964)	81%	1948, 1960, 1976

DATA APPENDIX

YEAR	VOTE2	FPRIME	FISCAL	GROWTH	ALLNEWS	DURATION	PARTY	INFLATION	PERSON
1880	50.22	-1	-1	3.879	9	1.75	-1	1.974	0
1884	49.85	-1	-1	1.589	2	2	-1	1.055	0
1888	50.41	-1	-1	-5.553	3	0	1	0.604	1
1892	48.27	1	1	2.763	7	0	-1	2.274	1
1896	47.76	1	-1	-10.024	6	0	1	3.41	0
1900	53.17	1	-1	-1.425	7	0	-1	2.548	1
1904	60.01	-1	-1	-2.421	5	1	-1	1.442	1
1908	54.48	-1	-1	-6.281	8	1.25	-1	1.879	0
1912	54.71	-1	-1	4.164	8	1.5	-1	2.172	1
1916	51.682	-1	-1	2.229	3	0	1	4.252	1
1920	36.119	1	1	-11.463	5	1	1	0	0
1924	58.244	-1	-1	-3.872	10	0	-1	5.161	1
1928	58.82	-1	-1	4.623	7	1	-1	0.183	0
1932	40.841	1	1	-14.499	4	1.25	-1	7.2	1
1936	62.458	1	-1	11.765	9	0	1	2.497	1
1940	54.999	-1	-1	3.902	8	1	1	0.081	1
1944	53.774	1	1	4.279	14	1.25	1	0	1
1948	52.37	-1	-1	3.579	5	1.5	1	0	1
1952	44.595	1	1	0.691	7	1.75	1	2.362	0
1956	57.764	-1	-1	-1.451	5	0	-1	1.935	1
1960	49.913	1	1	0.377	5	1	-1	1.967	0
1964	61.344	1	-1	5.109	10	0	1	1.26	1
1968	49.596	1	1	5.043	7	1	1	3.139	0
1972	61.789	-1	-1	5.914	4	0	-1	4.815	1
1976	48.948	1	1	3.751	5	1	-1	7.63	0
1980	44.697	1	-1	-3.597	5	0	1	7.831	1

1984	59.17	1	1	5.44	8	0	-1	5.259	1
1988	53.902	-1	-1	2.178	4	1	-1	2.906	0
1992	46.55	1	1	2.662	2	1.25	-1	3.28	1
1996	54.736	-1	-1	3.121	4	0	1	2.062	1
2000	50.27	-1	-1	1.219	8	1	1	1.605	0
2004	51.233	1	1	2.69	1	0	-1	2.325	1
2008	46.31	1	-1	0.22	3	1	-1	2.88	0
mean	52.09103	0.030303	-0.33333	0.624273	6	0.712121	-0.15152	2.666303	0.606061
s.d.	6.064975	1.015038	0.957427	5.455028	2.772634	0.66474	1.003781	2.1063043	0.496198