Predicting Elections from Biographical Information about Candidates:

A test of the index method

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Abstract

We used 59 biographical variables to create a "bio-index" for forecasting U.S. presidential elections. The bio-index method counts the number of variables for which a candidate rates favourably, and the forecast is that the candidate with the highest score would win the popular vote. The bio-index relies on different information and includes more variables than traditional econometric election forecasting models. The method can be used in combination with simple linear regression to estimate a relationship between the index score of the candidate of the incumbent party and his share of the popular vote. The study tested the model for the 29 U.S. presidential elections from 1896 to 2008. The model's forecasts, calculated by cross-validation, correctly predicted the popular vote winner for 27 of the 29 elections; this performance compares favourably to forecasts from polls (15 out of 19), prediction markets (22 out of 26), and three econometric models (12 to 13 out of 15 to 16). Out-of-sample forecasts of the two-party popular vote for the four elections from 1996 to 2008 yielded a forecast error almost as low as the best of seven econometric models. The model can help parties to select the candidates running for office, and it can help to improve on the accuracy of election forecasting, especially for longer-term forecasts.

Keywords: econometric model, election forecasts, forecast accuracy, index model, political forecasting political marketing, unit-weighting

This study examines the extent to which knowledge of biographical and demographic information about candidates allows for predicting the outcomes of U.S. presidential elections. Such an approach might prove useful for the selection of candidates as well as to improve the accuracy of election forecasts, especially long-term forecasts.

The index method

To address this problem, the data are analyzed with the index method. The index method asks analysts to prepare a list of key variables and to specify from prior evidence whether the variables are favorable (+1), unfavorable (-1), or indeterminate (0) in their influence on a certain outcome. Alternatively, the scoring can be 1 for a positive position and zero otherwise. Then, the analysts simply add the scores and use the total to calculate the forecast.

Researchers have used the index method for various types of forecasting problems. For example, Burgess (1939) applied the index method to predict the success of paroling individuals from prison. For each of 25 factors, the author rated whether the factor is "favorable" (+1) or "unfavorable" (0) and calculated an index score to determine the chance of successful parole.

The beginnings of the index method trace back to Benjamin Franklin. On September 19, 1972, Franklin wrote a letter to his friend Joseph Priestly, in which he described 'a method of deciding doubtful matters' that works similar to the index method (in Sparks, 1856, p.20).

Unlike Franklin's method, this study does not give consideration to the magnitudes of the ratings or to the effect size of the variables. While these issues can be addressed, prior research suggests that such factors have little impact on accuracy. Based on their analysis of linear models for four decision-making problems, Dawes and Corrigan (1974) concluded that the key to accuracy for non-experimental data in the social sciences is to select the proper variables and to assess the directions of effects.

Conditions for the index method

In using unit or equal weights, the analyst assesses the directional influence of a variable on the outcome by drawing upon evidence from prior research or experts' domain knowledge. If little knowledge exists, the analyst should question the relevance of including a variable in the model. Thus, the index method is particularly valuable in situations with good prior domain knowledge.

Analysts can incorporate an unlimited number of variables in an index model and can use whichever variables are relevant to the event being forecast. The ability to use all cumulative knowledge in a domain is an important advantage of the index method. One might call them "knowledge models."

In sum, the index method is valuable in situations involving many causal variables and good prior knowledge about the influence of the variables on the outcome. In contrast to the research on equal weights, the index method goes beyond a given set of data and enables the analyst to use all available knowledge.

Few researchers appear to be aware of the value of the index method. Prior to a talk at the *2009 International Symposium on Forecasting*, the authors conducted a small survey to ask researchers in the forecasting field for their expectations about the relative performance of the index method, multiple regression, and step-wise regression in situations with a large number of variables and few observations. On average, the 13 experts who rated themselves as high on 'expertise with forecasting methods' expected regression to yield the most accurate results, followed by the index method.

Use of the index method in election forecasting

Given that the number of potential variables is large and that a substantial body of knowledge exists about how certain factors influence voting, forecasting of U.S. presidential elections lends itself to the use of index models. In addition, data in this situation is limited to about 25 elections at most. Dana and Dawes (2004) analyze relative performance of multiple regression and unit weighting for five real social science datasets and a large number of synthetic datasets. The authors conclude that regression should not be used unless sample size is larger than 100 observations per predictor.

Cuzán and Bundrick (2009) apply an equal-weighting approach to three regression models: Fair's equation (Fair, 1978) and two variations of the fiscal model (Cuzán and Heggen, 1984). For the 23 elections from 1916 to 2004, the equal weighting scheme outperformed two of the three regression models – and performed equally to the third – when making out-of-sample predictions. For the full sample of 32 elections from 1880 to 2004, equal weighting yielded a lower mean absolute error than all three regression models.

Lichtman (2006) was the first to use the index method to forecast U.S. presidential election winners. His model, which uses 13 variables, provided correct forecasts retrospectively for all of 31 elections and prospectively for all of the last 7 elections. No econometric model achieved this level of accuracy in picking the winner of the popular vote. The Lichtman model uses the same variables for all elections and is based only on the judgments of a single rater, Lichtman.

Armstrong and Cuzán (2006) use simple linear regression to transform Lichtman's model into a quantitative model and to compare the model's ex ante forecasts to forecasts from three traditional regression models for the six U.S. presidential elections from 1984 to 2004. The transformed Lichtman model performed well and yielded forecast errors that were competitive to those of three established regression models. For the 2008 election, the forecast from Lichtman's model—issued in August 2007, more than a year before Election Day missed the actual outcome by only 0.3 percentage points —and was again more accurate than the out-of-sample forecasts derived from the same three models.

Biographical index

Table 1 provides an overview of the 59 variables that were used to compose a biographical index model. Based on perceived wisdom and findings from prior research, these variables were expected to have an influence on election outcomes. Details on these variables, along with sources, are provided in Appendix 1.

Table 1 about here

One example of a biographical variable that has value in predicting election outcomes is the perceived facial competence of candidates. Todorov, Mandisodza, Goren and Hall (2005) presented 31 subjects with pictures of candidates running in U.S. House and Senate elections. Based on one-second exposures, the subjects rated each candidate's competence. Subjects who recognized a candidate were excluded. For the three Senate elections from 2000 to 2004, the most competent-looking candidates won 71% of the 95 races. For the two House elections in 2002 and 2004, the most competent-looking candidates won 67% of the 600 races in their sample. In a similar study, Antonakis and Dalgas (2009) asked 684 university students and 2,814 children in Switzerland to rate pairs of black and white photos of faces of candidates in the 2002 French parliamentary election. In both samples, the candidates that achieved higher ratings on facial competence won in 72% of the elections. Similarly, Armstrong, Green, Jones and Wright (2010) found facial competence to be predictive for the outcome of the 2008 U.S. presidential primaries.

A few of the variables are fixed (e.g., height) while others are subject to change. For an example of variables that can be changed, consider the use of eyeglasses. A lab experiment found that people wearing eyeglasses are perceived to be more industrious, dependable, and honest (Thornton, 1944). Findings from another lab experiment show that eyeglasses can enhance an individual’s perceived authority (Bartolini, Kresge, McLennan, Windham, Buhr and Pryor, 1988).

People might not consciously evaluate all relevant traits when selecting their leaders. An example is birth order. Newman and Taylor (1994) analyze samples of 45 male U.S. Governors and 24 Australian prime ministers. Compared to the population at large, the politicians in both samples were more likely to be first-born and less likely to be middle-born. Similarly, Andeweg and Van Den Berg (2003) show that single children were overrepresented among a sample of almost 1,200 Dutch politicians, whereas middle-children were underrepresented. Another example is the experience of traumatic or adverse events like the early loss of a parent. Simonton (1999) reports on various studies that found that geniuses from various fields are more likely to be orphaned than the remainder of the population. For example, one of these studies found that 15 of 24 British prime ministers were orphans.

In sum, empirical research supports the relevance of numerous biographical traits for the emergence of leaders. Given the large number of variables, the index method is an appropriate choice for predicting election winners based on biographical traits.

Coding

Each variable was coded for whether the variable has a positive or negative influence on votes. There are two types of variables: (1) Yes / no variables indicate whether a candidate has a certain characteristic or not. Examples include whether a candidate is a single child, is married, or graduated from college. (2) Comparative variables incorporate information about the relative value of the variable for the candidates that run against each other in a particular election. Here, the candidate who achieves a more favorable value on a variable is assigned a score of 1 and 0 otherwise. Examples include candidates' height, intelligence, or attractiveness. Thus, the taller candidate would score a 1, and the shorter a 0.

Two independent coders rated the candidates. If these coders disagreed, a third coder made the final decision. (The final coding is available online at tinyurl.com/pollybio-coding.) The sum of variable values for each candidate in a particular election determines the candidate's *bio-index score* (B).

Data

Biographical data were collected on the candidates of the two major parties that ran for office in the 29 elections from 1896 to 2008. All data refer to the candidate's biography at the time of the respective election campaign, and were obtained from candidate's biographies, fact books, encyclopedias and earlier studies. For more information see Appendix 1.

Predictive performance of the bio-index

The bio-index incorporates two ways for predicting the outcome of elections: (1) a simple heuristic to predict the election winner and (2) a quantitative model to predict the popular two-party vote shares of the candidates running for office.

Heuristic based approach

To apply the heuristic, the analyst has to assess the direction for how a variable will influence the election outcome, assign values to the candidates, and then sum the values to calculate the index scores. The candidate with the higher bio-index score (B) is predicted as the winner of the popular vote.

Table 2 shows the candidates' index scores in each election year. For the 29 elections, the heuristic correctly predicted the winner 27 times and was incorrect twice. Thus, the proportion of correct forecasts (i.e., hit rate) is 0.93. The heuristic did not predict Bill Clinton to succeed George Bush in 1992, and, in 1976, the forecast wrongly predicted Gerald Ford to win against Jimmy Carter.

Table 2 about here

Bio-index heuristic versus polls

Campaign – or trial heat – polls reveal voter support for candidates in an election. Although polls are only assessments of current opinion or snapshots, their results are routinely interpreted as forecasts and projected to Election Day. For example, the trial-heat forecasting model by Campbell (1996) uses the economic growth rate and Gallup trial-heat polls as predictor variables. However, polls conducted early in the campaign are commonly seen as unreliable, which is why Campbell adjusts their results according to the historical relationship between the vote and the polls.

This study compares the performance of the bio-index to the predicted two-party vote shares from the final pre-election Gallup poll. The Gallup polling data for the 18 elections from

1936 to 2004 are published in the Appendix in Snowberg, Wolfers, and Zitzewitz (2007). For the 2008 election, the final pre-election poll was obtained from gallup.com. The hit rate, shown in Table 3, is the proportion of forecasts that correctly determined the election winner. Four times out of the last 19 elections, the final pre-election Gallup poll predicted the wrong candidate to win the election and thus yielded a hit rate of 0.79. By comparison, the bio-index heuristic failed twice for the same sample of 19 elections (a hit rate of 0.89).

Table 3 about here

Bio-index heuristic versus prediction markets

Prediction markets to forecast election outcomes have been popular since the late 19th century. Rhode and Strumpf (2004, p. 127) study historical betting markets that existed for the 15 presidential elections from 1884 through 1940 and concluded that these markets "did a remarkable job forecasting elections in an era before scientific polling". Since 1988, the Iowa Electronic Market (IEM), an internet-based futures market in which participants trade contracts on the outcome of future events, has provided forecasts of U.S. presidential election outcomes. Berg, Nelson and Rietz (2008) compared 964 polls to IEM forecasts for the five presidential elections from 1988 to 2004 and found that IEM forecasts were closer to the actual election results 74% of the time. However, this advantage disappeared when compared to combined and damped polls (Erikson and Wlezien, 2008).

The present study compares the bio-index to prediction market prices from the last day prior to Election Day. Prediction market data were available for 26 of the last 29 elections. For the period from 1896 to 1960, forecasts were taken from the historical Wall Street Curb markets as described in Rhode and Strumpf (2004). For the four elections from 1976 to 1988, the study analyzes betting odds from British bookmakers. Both data sets are published in the Appendix to Snowberg et al. (2007). For the last five elections from 1992 to 2008, the data include publicly available prices from the IEM. (For the three elections from 1964 to 1972, no prediction market was available.) The three datasets are slightly different. While the Wall Street Curb markets and the bookmakers predicted the Electoral College winner, the IEM provided a forecast of the popular vote winner. Nonetheless, each market provided winner-take-all prices. This price reflects the probability with which the market expects a candidate to win. For example, a market price of $80 indicates an 80% chance of winning. Thus, if the price of a candidate exceeds 50%, the market predicts this candidate to win the election. The results are shown in Table 3. The prediction markets achieved 22 (out of 26) correct predictions, which corresponds to a hit rate of 0.85, compared to 0.92 for the bio-index heuristic for the same elections.

Bio-index heuristic versus econometric models

Table 3 shows the hit rates of three well-established econometric models for which out-of-sample forecasts for early elections are available. The forecasts from these models were calculated by N-1 cross-validation. This means that the analyst used N-1 observations from the dataset to build the model and then made a forecast for the one remaining election. Abramowitz (1996) and Campbell (1996) publish cross-validated forecasts from 1948; Wlezien and Erikson's forecasts are available from 1952 (Wlezien, 2001). For the three most recent elections, *ex ante* forecasts, published before the actual Election Day, are available from the authors' respective publications in the elections symposia in *PS: Political Science and Politics*, 34(1), 37(4), and 41(4). In predicting 16 elections, Abramowitz's model failed four times, yielding a hit rate of 0.75. Both Campbell (16 elections) and Wlezien and Erikson (15 elections) missed the correct winner three times and achieve hit rates of 0.81 and 0.80, respectively. Compared to each of the three models, the bio-index heuristic yielded a higher hit rate, as shown in the last column of Table 3.

In sum, the forecasts from the bio-index heuristic—made in January of the respective election year— yielded a higher hit rate than forecasts from polls, prediction markets, and econometric models.

Predicting the vote share

Bio-indexes can also be used to build a model for forecasting the incumbent party candidate's percentage of the two-party vote. The relative bio-index score (P) of the candidate of the incumbent party represents the predictor variable. P is the percentage of variables that favored the candidate of the incumbent party and is defined as:

$$P = [B_{Incumbent} / (B_{Incumbent} + B_{Challenger})]*100.$$

We estimated a simple regression model using V, the actual two-party vote share received by the candidate of the incumbent party as the dependent variable. For the period from 1896 to 2008, this yielded the following vote equation:

$$V = 18.0 + 0.65 * P.$$

Thus, the model predicts that an incumbent would start with 18% of the vote, plus a share depending on P. If the percentage of biographical variables favoring the incumbent goes up by 10 percentage points, the incumbent's vote share will go up by 6.5%.

Accuracy of the bio-index model

Table 4 shows out-of-sample vote-share forecasts of the bio-index model, calculated by N-1 cross-validation. As with the heuristic-based approach, the model-based approach correctly predicted 27 elections and failed for the elections in 1976 and 1992. Over all 29 elections, the mean absolute error (MAE) of the bio-index model was 4.6 percentage points.

Table 4 about here

The bio-index model's forecasts of the winner were identical to those for the bio-index heuristic. Thus, the model's hit rate outperformed the polls, prediction markets, and econometric models.

Bio-index model versus econometric models

Because the bio-index model provides vote-share forecasts, the model's predictions can be compared to forecasts from econometric models. Given that the data are more extensive and more accurate for recent elections (remember that the econometric models suffer from small sample sizes), the comparison focuses on pure *ex ante* forecasts for the most recent four elections. That is, only data from elections prior to the respective election year were used for building the model. For example, to predict the 2008 election, data on the 28 elections from 1896 to 2004 were used; for the 2004 election, data on the 27 elections from 1896 to 2000 were used, and so on.

Table 5 shows such *ex ante* forecasts from the bio-index model and seven well-established econometric models. Most of these forecasts were published in *American Politics Quarterly* 24(4) and *PS: Political Science and Politics*, 34(1), 37(4), and 41(4). Fair reports the forecasts of his model on his website (fairmodel.econ.yale.edu). For an overview of the predictor variables used in most of the models, see Jones and Cuzán (2008).

The bio-index model performed well compared to the seven econometric models. Even though the bio-index model made its forecasts many months before most other models, the model yielded a MAE almost as low as that yielded by the most accurate econometric model. Since the bio-indexes of candidates basically never change during an election campaign, the results would be identical if one would compare forecasts made at around the same time.

Table 5 about here

Discussion

The bio-index model relies on prior studies and domain knowledge for choosing variables. Because the index method allows for an unlimited number of variables and does not weight variables, the analyst can use different variables when forecasting new events. For example, for predicting different-gender races, one might want to exclude variables that are only relevant for same-gender races (e.g., height and weight). Furthermore, the index method allows for adding variables once new information becomes available, for example, if a new variable is discovered that is not yet incorporated in the model (e.g., if a candidate was awarded the Nobel Peace Prize). This flexibility is an important advantage as the index method allows for using all cumulative knowledge in a domain.

When is a bio-index most effective?

In general, election forecasters consider open-seat elections (i.e., without an incumbent in the race) harder to forecast. For the elections from 1868 to 2004, Campbell (2008) compares the outcomes of the 13 open-seat elections to the 22 elections with an incumbent in the race. He finds that open-seat elections are more often near dead heats than elections with an incumbent running. Also, out of the 11 elections in his sample that were decided by a landslide, only two were open-seat.

A closer look at the performance of the three econometric models listed in Table 3 supports the speculation that traditional election forecasting models have difficulties in predicting open-seat elections. All three models failed to correctly predict the winner of the elections in 1960 and 1968; Campbell's model also missed the winner in 2008. Each of these elections was an open-seat election. By comparison, as shown in Table 4, the bio-index model correctly predicted the winner for each of the ten open-seat elections in our sample. Although drawing on a small sample, the results suggest that the bio-index model is helpful for predicting the outcome of open-seat elections.

Bio-indexes as nomination helper

The bio-index method can issue its forecast as soon as the candidates are known – or even before, conditional on who might run for office. Thus, bio-indexes can advise candidates whether they should enter the race and can help parties in nominating their candidates. Parties should select the candidate who achieves a high index score—possibly conditional to a specific opponent.

Bio-indexes are simple to use and easy to understand. For predicting the winner, a simple heuristic can be used that does not require information from previous elections. Bio-indexes can also be used in combination with regression to allow for quantitative vote predictions.

The index model would also be useful for many other problems involving a large number of variables, small data sets, and a good knowledge base. Examples include selection problems such as predicting which CEO a company should hire, where to locate a retail store, which product to develop, or whom to marry.

Conclusion

The present study applies the index method to the 29 U.S. presidential elections from 1896 to 2008 and provides forecasts based on biographic information about candidates. For 27 of the 29 elections, the bio-index heuristic and the bio-index model each correctly predicted the popular vote winner, a performance that is superior to polls, prediction markets, and three econometric models. In addition, the model's *ex ante* forecasts of the popular vote for the four elections from 1996 to 2008 yielded a forecast error almost as low as the best of seven econometric models.

In using a different method and drawing on different information than traditional election forecasting models, the bio-index model can contribute to forecasting accuracy. Bio-indexes are simple to use, easy to understand, and can help political parties in nominating candidates running for office.

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Table 1: Bio-index variables

No.	Variable	No.	Variable
1	Adopted children	31	Vice President
2	Ancestry	32	Disability
3	Children	33	Disease survivor
4	Divorce	34	Chronic illness
5	Father (political office)	35	Loss of children
6	First born	36	Loss of sibling
7	Single child	37	Loss of spouse
8	Marriage	38	Orphanhood
9	College	39	Age
10	College graduate	40	Athlete
11	Law degree	41	Book author
12	Master’s degree	42	Celebrity
13	PhD	43	Facial hair
14	Professor	44	Glasses
15	Phi beta kappa	45	Hair
16	Prestigious college	46	Military experience
17	U.S. Naval / Military Academy	47	Military honors
18	Attorney General	48	Gender
19	City major	49	Facial competence
20	Election defeat	50	First name
21	Governor	51	Height
22	Judge	52	Home state

23	Lieutenant Governor	53	IQ
24	Solicitor General	54	Physical attractiveness
25	State Representative	55	Race
26	State Senator	56	Religious affiliation
27	U.S. President	57	Surname
28	U.S. Representative	58	Voice
29	U.S. Secretary	59	Weight
30	U.S. Senator		

Table 2: Bio-index scores of presidential candidates (1896-2008)

(grey= incorrect forecasts)

Election year	Winner (W)	Loser (L)	Index score W	L
1896	McKinley	Bryan	19	13
1900	McKinley	Bryan	20	13
1904	Roosevelt	Parker	23	13
1908	Taft	Bryan	21	15
1912	Wilson	Taft	27	22
1916	Wilson	Hughes	25	19
1920	Harding	Cox	19	13
1924	Coolidge	Davis	22	21
1928	Hoover	Smith	18	14
1932	Roosevelt	Hoover	25	19
1936	Roosevelt	Landon	23	19
1940	Roosevelt	Willkie	22	13
1944	Roosevelt	Dewey	22	15
1948	Truman	Dewey	20	16
1952	Eisenhower	Stevenson	20	14
1956	Eisenhower	Stevenson	21	14
1960	Kennedy	Nixon	28	18
1964	Johnson	Goldwater	24	16
1968	Nixon	Humphrey	21	15
1972	Nixon	McGovern	23	20

1976	Carter	Ford	21	26
1980	Reagan	Carter	21	20
1984	Reagan	Mondale	22	17
1988	Bush H	Dukakis	27	20
1992	Clinton	Bush	22	24
1996	Clinton	Dole	27	16
2000	Gore*	Bush	23	20
2004	Bush	Kerry	23	21
2008	Obama	McCain	25	20

* based on the popular vote

Table 3: Hit rate of the bio-index heuristic forecasts (made in January) and benchmark approaches

Benchmark method	Approx. date of forecast	Sample of Elections	Benchmark method: Correct forecasts	Benchmark method: Hit rate	Bio-index hit rate (same sample)
Gallup poll	Final poll	19	15	.79	**.89**
Prediction markets	Final market price	26	22	.85	**.92**
Econometric Models					
Abramowitz (1996)	Late July / early August	16	12	.75	**.88**
Wlezien & Erikson (Wlezien 2001)	Late August	15	12	.80	**.87**
Campbell (1996)	Early September	16	13	.81	**.88**

Note: most accurate forecast in bold

Table 4: Out-of-sample forecasts of the bio-index model and actual election outcomes (grey: incorrect forecasts)

Election year	Open-seat election	Incumbent party candidate's share of two-party popular vote: Actual	Predicted	AE
1896	1	47.3	43.8	3.5
1900	0	53.2	57.4	4.3
1904	0	60.0	59.1	0.9
1908	1	54.5	55.7	1.2
1912	0	35.6	47.8	12.2
1916	0	51.7	54.8	3.1
1920	1	36.2	45.3	9.2
1924	0	65.2	50.5	14.7
1928	1	58.8	54.1	4.7
1932	0	40.9	46.3	5.5
1936	0	62.5	53.0	9.5
1940	0	55.0	59.0	4.0
1944	0	53.8	56.5	2.8
1948	0	52.4	53.9	1.5
1952	1	44.6	44.6	0.0
1956	0	57.8	56.6	1.1
1960	1	49.9	42.1	7.8
1964	0	61.3	56.4	5.0
1968	1	49.6	44.3	5.3
1972	0	61.8	52.2	9.6
1976	0	48.9	53.9	4.9
1980	0	44.7	49.7	5.0
1984	0	59.2	54.2	5.0
1988	1	53.9	55.1	1.2
1992	0	46.5	51.8	5.3

1996	0	54.7	58.9	4.2
2000	1	50.3	52.6	2.3
2004	0	51.2	51.7	0.5
2008	1	46.3	46.7	0.4
Sum	**10**	**-**	**MAE**	**4.6**

Table 5: Bio-index model vs. quantitative models: Errors of out-of-sample forecasts (1996-2008, calculated through successive updating)

		Forecast error				
Model	**Approximate date of forecast**	**1996**	**2000**	**2004**	**2008**	**MAE**
Bio-index model	January, or as (potential) candidates are known	4.3	2.4	**0.5**	**0.4**	1.9
Econometric models						
Norpoth	January	2.4	4.7	3.5	3.6	3.5
Fair	Late July	3.5	**0.5**	6.3	2.2	3.1
Abramowitz	Late July / early August	2.1	2.9	2.5	0.6	2.0
Lewis-Beck and Tien	Late August	**0.1**	5.1	1.3*	3.6	2.5
Wlezien and Erikson	Late August	0.2	4.9	**0.5**	1.5	***1.8***
Holbrook	Late August / early September	2.5	10.0	3.3	2.0	4.4
Campbell	Early September	3.4	2.5	2.6	6.4*	3.7
	MAE					3.0

* incorrect prediction

Note: most accurate forecasts in bold

Appendix 1: The variables

Variable No.	**Variable**	**Coded as 1 if candidate (otherwise: 0)**	**Explanations**
		YES / NO VARIABLES	
		Family	
1	Adopted children	Has adopted children	See children. Voters might favor candidates who adopted children.
2	Ancestry	Descends from a presidential family	Descent from renowned families has been shown to have a positive impact on an individual's career chances (Simonton, 1984).
3	Children	Has children	Being the social norm to have children, voters might favor candidates who have children.
4	Divorce	Has *not* been divorced	Although divorces are common, they violate the social norm.
5	Father (political office)	Has a father who held a political office	The role of a candidate's father may have an impact of a candidate's chances to be elected. Similar to Simonton (1981), a score of 1 was assigned if a candidate's father held one of the offices listed from questions 18 to 31.
6	First born	Is the first-born child in	Simonton (1984) summarizes research showing that first-born children tend to achieve more

Variable No.	Variable	Coded as 1 if candidate (otherwise: 0)	Explanations
		his family	than later-born children. Newman and Taylor (1994) analyze samples of 45 male U.S. Governors and 24 Australian prime ministers. Compared to the population at large, the politicians in both samples are more likely to be first-born and less likely to be middle-born.
7	Single child	Is the single child	Single children have an advantage over children from larger families. For example, Simonton (1981) finds a negative correlation between family size and political performance for the 38 U.S. presidents up to Jimmy Carter. Andeweg and Van Den Berg (2003) analyze birth-order data for almost 1,200 Dutch politicians. Compared to the general population, they find single children to be overrepresented, whereas middle-children were underrepresented.
8	Marriage	Is married	It is the social norm to get married.
		Education	
9	College	Went to college	Similar to Simonton (1981), the level of formal education is coded by assigning values of 1, if a candidate went to college, graduated from college, obtained a Master's degree, obtained a PhD degree, obtained a Law (J.D.) degree, or worked as a university professor.
10	College graduate	Graduated from college	

Variable No.	Variable	Coded as 1 if candidate (otherwise: 0)	Explanations
11	Law degree	Has a Law (J.D.) degree	
12	Master's degree	Has a Master's degree	
13	PhD	Has a PhD / doctoral degree	
14	Professor	Has been a college or university professor	
15	Phi beta kappa	Is member of Phi beta kappa	Similar to Simonton (1981), scholastic performance is measured by quantifying whether a candidate was an in-course (not alumnus or honorary) member of Phi Beta Kappa.
16	Prestigious college	Attended an Ivy-League college	To have an objective and unambiguous criterion for the reputation of a college, all Ivy-League colleges as well as the U.S. Naval and Military Academies were considered as prestigious.
17	U.S. Naval / Military	Went to U.S. Naval / Military Academy	

Variable No.	Variable	Coded as 1 if candidate (otherwise: 0)	Explanations
	Academy		
		Political life	
18	Attorney General	Is / was U.S. or State Attorney General	
19	City major	Is / was a city major	
20	Election defeat	Has *not* been defeated in a political election	
21	Governor	Is / was a state governor	Similar to Simonton (1981), prior political experience was assessed by assigning values of 1 if a candidate had occupied one of the offices listed on the left.
22	Judge	Is / was a judge	
23	Lieutenant Governor	Is / was Lieutenant Governor	
24	Solicitor General	Is / was U.S. Solicitor General	

Variable No.	Variable	Coded as 1 if candidate (otherwise: 0)	Explanations
25	State Representative	Is / was a state representative	
26	State Senator	Is / was a state senator	
27	U.S. President	Is / was U.S. president	
28	U.S. Representative	Is / was a U.S. representative	
29	U.S. Secretary	Is / was a U.S. Secretary	
30	U.S. Senator	Is / was a U.S. senator	
31	Vice	Is / was Vice President	

Variable No.	Variable	Coded as 1 if candidate (otherwise: 0)	Explanations
	President	of the U.S.	
		Traumatic / adverse experiences	
32	Disability	Suffers from physical or sensory disability	Traumatic experiences that may have a positive impact on leader emergence may be the survival of a major life-threatening disease, physical or sensory disability, or chronic illness in childhood (Simonton 1999, p.115).
33	Disease survivor	Survived a major life-threatening disease	
34	Chronic illness	Has suffered from chronic illness in childhood or adolescence (before the age of 30)	
35	Loss of children	Has lost one or more children	Simonton (1999, p.115) reports empirical evidence that supports the idea that the development of genius may be enforced by traumatic experiences, particularly in childhood or adolescence.

Variable No.	Variable	Coded as 1 if candidate (otherwise: 0)	Explanations
36	Loss of sibling	Has lost one or more siblings	He refers to literature that finds people, who lost a parent during childhood, to be more likely to achieve more in life. Following Simonton (1981), a candidate is considered an orphan if one (or both) of his parents died before the age of 30. Similarly, scores of 1 are assigned if a candidate lost one (or more) children, siblings, or a spouse.
37	Loss of spouse	Has lost a spouse	
38	Orphanhood	Is an orphan	
		Other	
39	Age	Is between 47 and 64 years old	Candidates might have a disadvantage if they are either too young or too old. Prior research supports this assumption for high-level positions in large public firms. In analyzing a sample of more than 10,000 CEOs, Nelson (2005) finds that the median age was 57 years, the 10th percentile 47 years, and the 90th percentile 64 years.
40	Athlete	Is known as athletic	In his review of the literature, Stogdill (1948) summarizes several studies that found a positive relationship between leadership and athletic ability.
41	Book author	Has authored one or	The number of books that a president published prior to be elected has been found to have a

Variable No.	Variable	Coded as 1 if candidate (otherwise: 0)	Explanations
		more books	positive impact on his political performance (Simonton 1981). In addition, a publishing record should have a positive impact on the wide recognition of a candidate among voters.
42	Celebrity	Is / was a celebrity in a field other than politics	Being a famous person in a field other than politics should have a positive impact on the wide recognition of a candidate among voters. This can include being a famous actor, athlete, artist, or TV (radio) moderator.
43	Facial hair	Is clean-shaved	Several studies examine how facial hair (i.e. clean-shaved, mustache, goateed, beard) influences perception of people. For example, in their experimental study, Terry and Krantz (1993) find beards to be associated with lessened competence. Findings from an experiment by Shannon and Stark (2003) show that the rate of bearded applicants that are selected for management positions is lower compared to non-bearded applicants. By comparison, results from an experiment by Reed and Blunk (1990) find consistently more positive perceptions of social/physical attractiveness, personality, competency, and composure for men with facial hair. Given that most politicians, especially in recent years (note that William Taft was the last

Variable No.	Variable	Coded as 1 if candidate (otherwise: 0)	Explanations
			U.S. president with facial hair), are clean shaved, facial hair is expected to have a negative effect on the evaluation of candidates.
44	Glasses	Wears glasses	In analyzing results from a lab experiment, Thornton (1944) finds people wearing eyeglasses to be perceived more industrious, dependable, and honest. Another lab experiment finds that eyeglasses enhance an individual's perceived authority (Bartolini et al.1988). Terry and Krantz (1993) find eyeglasses to be associated with heightened competence but also diminished forcefulness. Eyeglasses were expected to have a positive impact on the evaluation of candidates.
45	Hair	Is not bald	Although not identifying a voter bias, Sigelman et al. (1990) find that bald and balding men are underrepresented among governors and Congress members as compared to the general public.
46	Military experience	Has military experience	Similar to Simonton (1981), military experience is coded if a candidate served as wartime recruit, professional soldier, or military general.
47	Military	Has been awarded with	Scores of 1 are assigned if a candidate was awarded with military honors.

Variable No.	Variable	Coded as 1 if candidate (otherwise: 0)	Explanations
	honors	military honors	
48	Gender	Is male	In their meta-analysis, Eagly & Karau (1991) find men to emerge more often than women as leaders from initially leaderless groups. This goes back to the fact that leadership is perceived in terms of male stereotypical characteristics, which makes it more difficult for women to emerge as leaders.
		COMPARATIVE VARIABLES	
49	Facial competence	Is more competent	Several studies measure competence ratings based on people's assessments of candidates' headshots (Todorov et al., 2005, Antonakis & Dalgas, 2009). These studies show that candidates with higher ratings of 'facial competence' are more likely to win elections. Evaluations of facial competence are available for the 2004 (Little et al., 2007) and 2008 elections (Armstrong et al., 2010).
50	First name	Has the more common first name	Candidates with the more common first name were expected to have an advantage. Name popularity was obtained from 1990 U.S. census (http://names.mongabay.com).

Variable No.	Variable	Coded as 1 if candidate (otherwise: 0)	Explanations
51	Height	Is taller	Height is a well-known predictor for leadership emergence and performance. In their meta-analysis, Judge & Cable (2004) find physical height to be positively correlated to esteem (r=.41), leader emergence (r=.24), performance (r=.18), and income (r=.26). In estimating factors to predict presidential greatness, both McCann (1992) and Simonton (1981) find a positive correlation between height and political performance.
52	Home state	Is from the state with more electoral votes	Candidates are likely to win the votes of their home state. Thus, the candidate coming from the state with more electoral votes was assumed to have an advantage. The numbers for electoral votes by states in each election were derived from http://www.archives.gov/federal-register/electoral-college/votes/votes_by_state.html.
53	IQ	Is more intelligent	Results from a meta-analysis show that intelligence predicts leader emergence (Lord et al., 1986). Simonton (2006) correlates IQ scores for all 42 U.S. Presidents before Barack Obama with evaluations of presidential leadership performance. He found that intelligence is positively correlated with political success. IQ scores for 42 presidents were obtained from Simonton

Variable No.	Variable	Coded as 1 if candidate (otherwise: 0)	Explanations
			(2006). Where available, information from polls, which ask voters about which candidate appears more intelligent, was used by searching the iPoll Databank of the Roper Center.
54	Physical attractiveness	Is more attractive	King & Leigh (2009) assess the beauty of political candidates from major political parties and then estimate the effect of beauty on vote share for candidates in the 2004 Australian election. They find that beautiful candidates are more likely to win elections. Berggren et al. (2010) report a similar effect. In analyzing more than 10,000 visual assessments of almost 2,000 Finnish political candidates, the authors report a positive relationship between attractiveness and the received vote share of candidates. Attractiveness scores for 39 presidents were obtained from Simonton (1986). The coding for the 1920 election race between Harding and Cox is based on Gladwell (2005). Where available, information from polls, which ask voters about which candidate is more attractive, was used by searching the iPoll Databank of the Roper Center.
55	Race	Represents the larger	Voters were expected to more likely endorse a candidate that represents their race. Thus, the

Variable No.	Variable	Coded as 1 if candidate (otherwise: 0)	Explanations
		race	candidate that represents the larger race was expected to have an advantage. Also, in analyzing ballot photographs for low-information elections, Banducci et al. (2008) find that the probability of winning for white candidates is 38% greater than for nonwhite candidates.
56	Religious affiliation	Is affiliated with the larger religion	Voters were expected to more likely endorse a candidate that identifies with their religious beliefs. Thus, the candidate that identifies himself with the larger religion was expected to have an advantage.
57	Surname	Has the more common surname	Candidates with the more common surname were expected to have an advantage. Name popularity was obtained from 1990 U.S. census (http://names.mongabay.com).
58	Voice	Has the more dominant voice	Gregory & Gallagher (2002) analyze the acoustic frequency of candidates' voices in presidential debates. The authors find that this nonverbal vocal communication reveals social dominance and thus can be helpful to predict the popular vote. This study uses the data from the eight elections in their sample for our analysis.
59	Weight	Is heavier	In his review of the literature, Stogdill (1948) provides evidence that weight is positively

Variable No.	Variable	Coded as 1 if candidate (otherwise: 0)	Explanations
			correlated with leadership (r = .23): seven studies find leaders to be heavier, whereas two studies find leaders to be lighter; another two studies find no difference.

Appendix 2: References for Appendix 1, not cited in the main paper

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