Election Forecasting

GRAD-E1234

Fundamentals Models

or:

"There is no 'fun' in fundamentals models."

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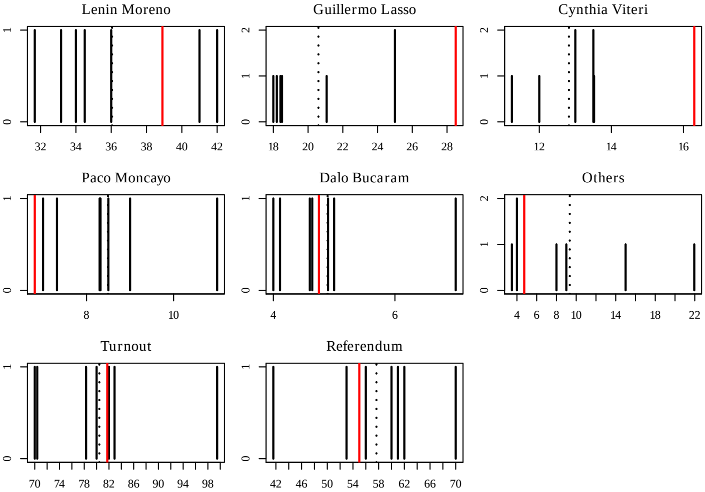
Spring Semester 2017
Humboldt-University of Berlin

Session outline

Election forecast of last week



Election forecast of last week

rank	respondent	mae	rmse	time
1	Victoria Dykes	2.71	2.93	15
2	Moritz Hemmerlein	3.28	4.49	40
3	Nadina Iacob	4.29	5.54	25
4	Nauel Semaan	4.61	5.87	45
5	Christoph Abels	5.11	7.52	30
6	Alexander Sacharow	5.80	7.83	10
7	Hendrik Frank	6.78	8.89	30

Election forecast of last week

rank	note
1	Recent polls on the presidential candidates were easy to find; it sounds like Moreno is likely to lead but not secure the margin necessary to avoid a second round. I found it harder to find data on the referendum; the current president supports it and he seems to be fairly popular; so I am assuming this translates into some level of mass support for the measure; but am not sure to what extent.
2	I took all available recent polls an averaged them. Moreover; I adjusted the average values by some thoughts of mine. Most important; I don't regard the loss due to the "Correa-Bonus" to be as bad as predicted. Therefore; I expect Moreno's share to be little higher than predicted by the polls. Consequently; the opponents shares will be little lower.
6	Averaging last weeks / recent polls. For referenduum just a random guess.
7	For the Presidential election I used the "wisdom of the crowd" and aggregated the polling results of the 6 latest polls. Regarding the turnout I looked at previous turnouts and made the guess that the turnout would decrease because Correa is not allowed to run. For the referendum I looked at who supports and opposes the measure. Given that the opposition mainly rejects the measure and that its candidates are collectively polling higher than Moreno; I believe that the referendum will not pass.

Fundamentals models

The logic of fundamentals models

- outcome of elections is result of individual voting behavior
- $\rightarrow$ exploit well-known determinants of voting
- $\rightarrow$ translate individual-level predictors to macro-level indicators
- generic model of voting behavior:

$$\text{Vote} = f(\text{politics, economics})$$

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Generic procedure

- select subset of most powerful predictors, motivated by theory or R^2-hacking (limited d.f.! usually N < 20 in established democracies)
- train the model using past electoral data
- use trained model (weights a.k.a. estimated coefficients) and predictor values to forecast unknown outcome

The logic of fundamentals models

- first models of that style: Sigelman (1979), Lewis-Beck & Rice (1982), Rosenstone (1983)
- popular explanatory variables:
  - party/incumbent popularity
  - economic measures (GDP growth, GNP growth, perception of personal finances, prospective personal finances, income growth, job growth, ...)
  - incumbency status / term limits / time party has been in power
- popular underlying theoretical rationales: economic voting, partisan voting (also: easy to operationalize)
- example: Abramowitz' "time-for-a-change" model:

Model A, by Abramowitz (2004), is as follows in this OLS regression:

$$V = 50.75 + \underset{(0.025)}{0.107^{*}P} + \underset{(0.183)}{0.818^{*}E} - \underset{(1.24)}{5.14^{*}T} + e \qquad \text{(Eq.4)}$$

R-squared = 0.90 SEE = 2.00 N = 14 (elections 1948–2000)

where V = the incumbent's share of the two-party popular vote, P = presidential approval minus presidential disapproval in the last June Gallup poll, E = annualised growth rate of real GDP in the first two quarters of the election year, T = a term dummy, scored '1' if the president's party has been in the White House for more than one term, '0' otherwise; the figures in parentheses are standard errors, * = statistically significant.

Fundamentals forecasts for the 2016 US presidential election

Table 2

Summary of the 2016 PS Presidential Election Forecasts

Forecasters	Model(s)	Predicted Two-Party Popular Vote for Clinton	Certainty of Popular Vote Plurality	Days Before Election
Abramowitz	Time for a Change	48.6%	66%	102
Campbell	Trial Heat and Economy	50.7% Labor Day/Economy	69%	60
	Convention Bump and Economy	51.2% Con. Bump/Economy	75%	74
Graefe, Amstrong, Jones, and Cuzan	Pollyvote (combining forecasts)	52.7%	–	63
Holbrook	National Conditions and Trial Heat	52.5%	81%	61
Jerôme and Jerôme-Speziari	State-by-State Political Economy	50.1%	50%	121
Lewis-Beck and Tien	Politics, Economics and Institutions Presidential Forecast	51.1%	83%	102
Lockerbie	Economic Expectations and Political Punishment	50.4%	62%	133
Norpoth	The Primary Model	47.5%	87%	246
Wlezien and Erikson	Leading Economic Indicators and the Polls	52.0% Post-Conventions	82%	83
		51.8% Pre-Conventions	72%	119

"Although each model has its own track record and the accuracy of each forecast should stand judgment on its own, as background, it is worth bearing in mind that many of these forecasts were quite accurate in the 2012 election." – Campbell 2016, PS: Political Science & Politics 49(4)

Gschwend and Norpoth's Chancellor model

Background

- one of the first fundamentals models for German election
- long-term, medium-term, and short-term component
- quantity of interest: combined vote share of the outgoing coalition parties

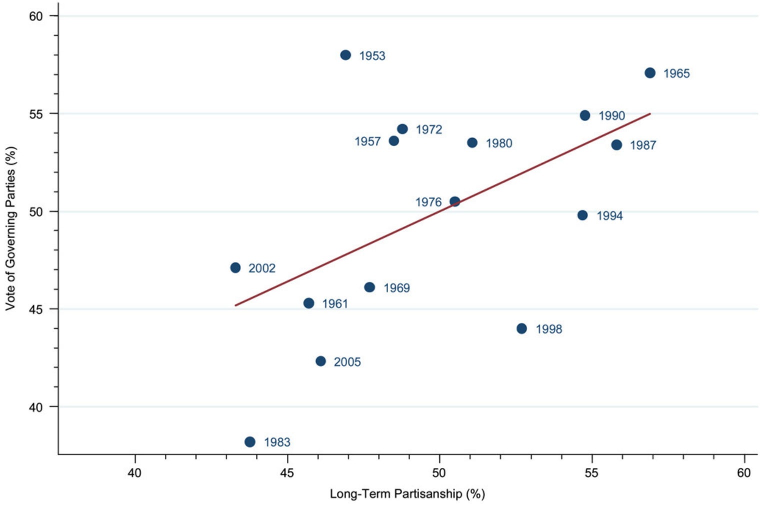
$$\text{STIM} = -5{,}93 + 0{,}75 \times (\text{PAR}) + 0{,}38 \times (\text{KAN}) - 1{,}52 \times (\text{AMT})$$

STIM: Stimmenanteil der Regierungsparteien bei einer Bundestagswahl
PAR: Langfristige Parteiunterstützung (Mittel der Stimmenanteile der Regierungsparteien bei den letzten drei Bundestagswahlen)
KAN: Kanzlerunterstützung (Mittelwert, unter Ausschluss von Unentschlossenen, ein und zwei Monate *vor* der Wahl)
AMT: Amtsperiode der Regierung

Performance

- 2002: forecast: SPD/Greens 47.1%, result: 47.1%
- 2005: forecast: SPD/greens 42.0%, result: 42.3%
- 2009: forecast: CDU/CSU/FDP 52.9%, result: 48.4%
- 2013: forecast: CDU/CSU/FDP 51.2%, result: 46.3% (FDP included)

Gschwend and Norpoth's Chancellor model



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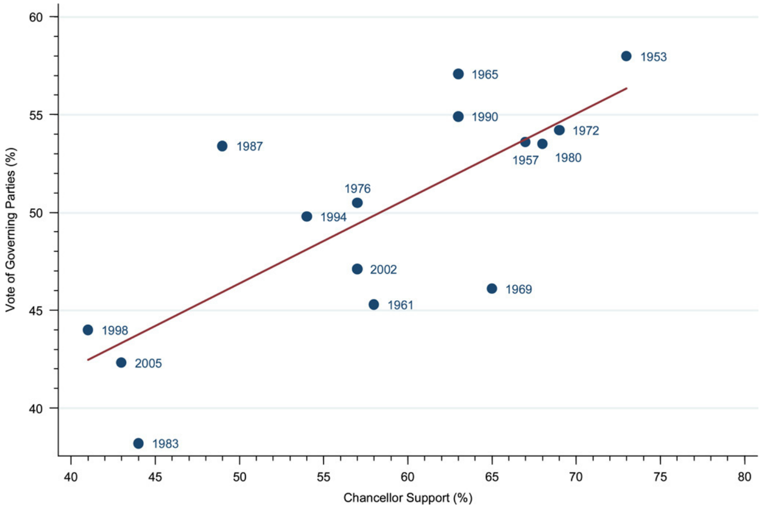

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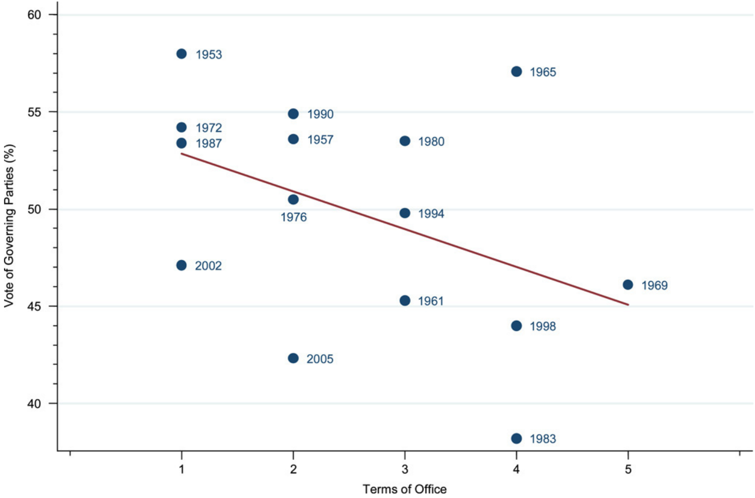

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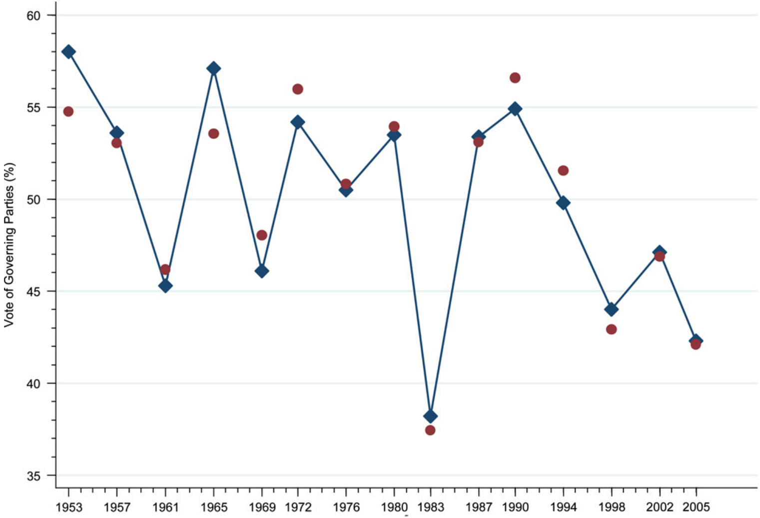

Fig. 5. The vote of governing parties with point forecasts.

Gschwend and Norpoth's Chancellor model

Extensions

- relative economic performance (Kayser and Leininger 2016)
- unemployment, vote intention polls (Jérôme et al. 2013)

Gschwend and Norpoth's Chancellor model

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Critique (Klein 2005)

- ad-hoc adaptation: chancellor support adjusted by share of Left party
- how idiosyncratic is the adaptation–why not translate the underlying rationale to earlier elections?

Discussion

- what are the quantities of interest in the German federal election?
- how could a fundamentals model be extended in the German case to provide forecasts for all major parties' vote shares?

Discussion

Discussion

Question 1

What are advantages and disadvantages of fundamentals models?

Question 2

What are useful criteria to evaluate forecasting models? Go beyond Lewis-Beck (2005) in your discussion!

Question 3

What is the quantity of interest of election forecasts? What role do features of the electoral system play? Use the German federal election and the US presidential election as examples!

Forecasting benchmarks

Lewis-Beck (2005) on forecasting model evaluation

Criteria

- accuracy (A, rated 0–2)
- lead time (L, rated 0–2)
- parsimony (P, rated 0–2)
- reproducibility (R, rated 0–2)

Overall quality index:

$$Q = \frac{(3A+P+R)L}{M}$$

Critical perspectives

Critique: van der Eijk (2005)

- sparseness of aggregate level models unsatisfactory (are left-out factors just noise?)
- lack of strong theory: incumbent popularity, economic performance not obvious macro-level equivalent for individual-level behavior
- functional specification (often linear) overly naïve
- little to be learned from forecasting exercise in theoretical terms; grotesque simplification of decades of research on voting behavior

Critique: Lauderdale and Linzer (2015)

Diagnosis

most fundamentals-based forecasts

- overstate confidence
- neglect alternative variable operationalizations, combinations, ...
- disregard implications of the electoral system (popular vote ≠ electoral college!)

Sources of uncertainty

- estimation of coefficients
- model specification
- correlation structure of outcomes at lower levels

Critique: Lauderdale and Linzer (2015)

Estimation uncertainty

- intuition: predicted values (and derived winning probabilities) based on fitted models come with uncertainty
- models are trained on known ys and Xs; y is unknown for future election and weights for X come with estimation uncertainty
- task: how to construct uncertainty interval around predicted values?
- standard approach
  - run OLS on previous elections; extract coefficients and $\hat{\sigma}$, the estimated conditional standard deviation of y given X
  - compute $\hat{y}_T$ based on weights
  - compute confidence interval $PI_{1-\alpha} = \hat{y}_T \pm t_{\alpha/2,n-k-1} \cdot \hat{\sigma}$
  - $\hat{\sigma} = s \cdot \sqrt{1/n}$ (s.e. of the fit)
- but: out-of-sample forecast more uncertain than in-sample point fit
- $\hat{\sigma}$ replaced with $\hat{\sigma}^* = s \cdot \sqrt{1 + 1/n}$ (s.e. of the prediction)
- $\hat{\sigma} < \hat{\sigma}^* \rightarrow$ prediction intervals always wider than confidence intervals

Critique: Lauderdale and Linzer (2015)

Specification uncertainty

- multitude of variable combinations possible (see also Gelman/King 1993)
- transformation of variables, functional form
- universe of possible models
- N limited → subset of variables needed
- solutions: model averaging, variable permutation, variable selection/regularization techniques (lasso, boosting, bagging)

Lauderdale and Linzer (2015): A state-level Bayesian forecasting model

- variable selection: regularization strategy using Bayesian priors
- electoral system: state- and national-level predictors, dynamic "normal votes"

Let y_{st} denote the Democratic share of the major-party vote in state s and election t. Extrapolating from elections $t = 1 \ldots T-1$, we wish to forecast the outcome of an upcoming election T, represented by unknown vote shares y_{sT}. We model y_{st} as a function of the national- and state-level covariates X and Z, and the state- and election-level random effects α and δ:

$$y_{st} = \alpha_{st} + \sum_k \beta_k x_{kt} + \sum_l \gamma_l z_{lst} + \delta_t + \epsilon_{st}. \quad (3)$$

The coefficients β_k are the effects of national-level variables on vote shares in all states, while the coefficients γ_l are the effects of state-level variables on the relative vote shares between states.

The random effect α_{st} captures states' persistent tendency to vote for one party or the other. States' party affinities drift over time, so we allow the magnitude of α_{st} to vary from one election to the next as a Bayesian dynamic linear model (West & Harrison, 1997):

$$\alpha_{st} \sim \mathcal{N}(\alpha_{s,t-1}, \sigma_\alpha) \quad (4)$$

$$\sigma_\alpha \sim \mathcal{N}_{1/2}(\sigma). \quad (5)$$

To guard against over-estimating the effects of the predictors and over-fitting the model, we assume priors for the national-level and state-level regression coefficients that are normally distributed with mean zero, and place a half-normal prior on the standard deviation of that distribution:[7]

$$\beta_k \sim \mathcal{N}(0, \sigma_\beta) \quad (8)$$

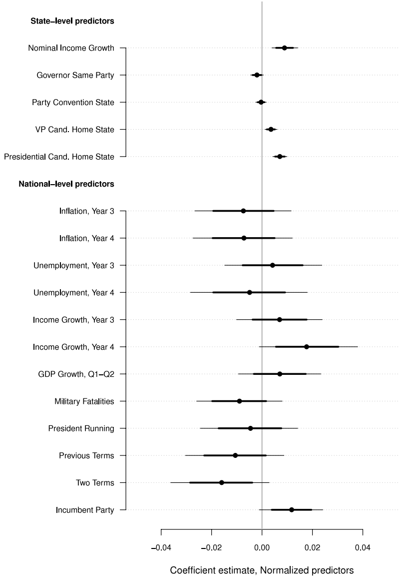
$$\sigma_\beta \sim \mathcal{N}_{1/2}(\sigma) \quad (9)$$

$$\gamma_l \sim \mathcal{N}(0, \sigma_\gamma) \quad (10)$$

$$\sigma_\gamma \sim \mathcal{N}_{1/2}(\sigma). \quad (11)$$

This approach allows us to use many more predictive variables than would be possible in a standard analysis, as we are estimating the distribution of coefficient magnitudes and constraining the coefficients accordingly. Our expectation that some (but not all) of these economic and political variables matter is reflected in their common prior.

Lauderdale and Linzer (2015): A state-level Bayesian forecasting model



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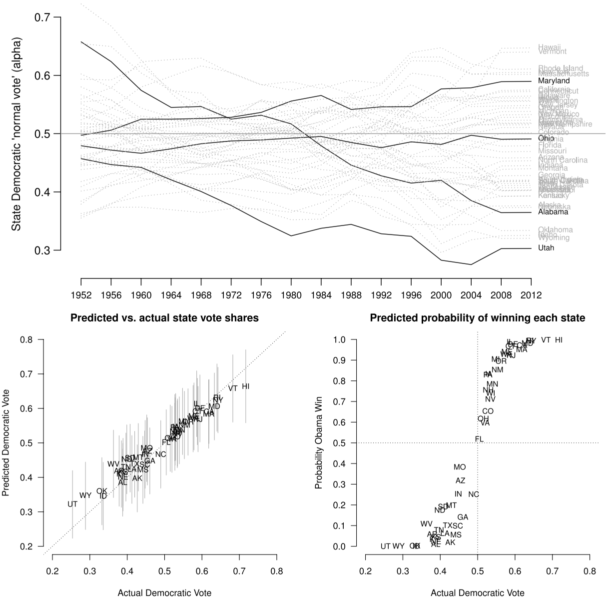

Implementing fundamentals models with R

Implementing fundamentals models with R

See R script!

See you next week!