Structural and Trial-Heat Model Combinations to Forecast US Elections

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1. Election Forecasting

Problem

Producing **timely and accurately prediction** of election results

Strategical task in the political area since political forces spend millions of dollars in each candidate's campaign and need to know when and where to allocate them

The **US**: presidential election is the result of the voting process in each state

2. Data

Type of Data

Forecasting elections makes use of mainly two different types data:

- **Fundamental indicators**, that is economic or political variables
- **Trial-heat polls**, that is surveys with trail-heat questions issued by official pollsters' agency

Fundamental Indicators

The **economy** strongly affect and anticipate election results. Among the most used economic indicator there are GDP, GNP, unemployment, inflation at national or state level

The **political dimension** of election is also of high relevance and it is usually measured by incumbency, time-for-change, votes of previous elections, presidential home-state advantage, president approval rating

Many models have been developed using only such data and predicted the results within few percentage points

Trial-Heat Polls

Survey responses are related to actual voting process, meaning that polls are connected to observable political behaviours and incorporate the process of updating information of individuals, so that can be used to track the evolution of preferences over time and states

Election polls data suffers of some **well-known problems** such as sampling errors, house effect, question wording, response errors and high variability

Nowadays many pollster agencies exist, producing surveys both at the national and state levels, in particular during the election year

3. Methods

Type of Models

Over the years, three types of election forecasting models evolved:

- **Structural models**, econometric models based on fundamental indicators
- **Trial-heat models**, econometric models relying on polls data
- **Bayesian models**, models that use polls data to update historical forecasts, improving the performance of structural models through the incorporation of voters preferences' evolution

The variable of interest is usually the percentage election outcome of one of the two major parties

Structural Models

The **Time-for-change model** is one of the most successful and was proposed by Abramowitz in 1988 (and again in 1996 and 2008)

$$Y_t = \beta_0 + \beta_1 GDP_{t-1} + \beta_2 Approval_t + \beta_3 TC_t$$

It assumes that voters positively evaluate periodic government alternation of the two major parties

It relies only on previous elections' data without incorporating the opinion about the current election

Trial-Heat Models

Using trial-heat polls as **literal forecast** produce very poor results, because the accuracy of election polls depends enormously on when the poll is conducted

Gelman and King incorporated current polls information within a more complex structural model considering the aggregate trial-heat two months before the election, incumbency, GNP rate, approval rating and state variables

Campbell improved the poor trial-heat literal prediction suggesting a simple regression model that used only trial-heat polls at national level

Bayesian Models

Since the late 90s, methods implementing a Bayesian approach have been introduced also in the context of election prediction

Bayesian models naturally follow the **“voters’ enlightenment”** hypothesis because the weights voters attach to fundamental variables are allowed to change during the campaign, accounting for changes in public opinion

Core idea: to use polls data to update historical forecasts, accounting for current voters’ preferences and improving the performance of structural models

Bayesian Models - Rigdon et al.

- Assumes that the beliefs about election's outcomes are based on historical voting trends
- Considers the proportions of **third-party candidates and undecided**
- A **Dirichlet-Multinomial** model with a conjugate prior based on past election results and a likelihood based on current poll data to estimate each candidate's probability of winning a state

Bayesian Models - Rigdon et al.

$$X = (X_1, X_2, X_3, X_4) \sim Multinomial(n, p_1, p_2, p_3, p_4)$$

$$p = (p_1, p_2, p_3, p_4) \sim Dirichlet(b_1, b_2, b_3, b_4)$$

where X_i are the sample proportions in a state poll and p_i are the shares in a state of candidate i

$$P(p|X) \sim Dirichlet(x_1 + b_1, x_2 + b_2, x_3 + b_3, x_4 + b_4)$$

The choice of parameters is based on historical election reasoning.

Bayesian Models - Linzer

- The quantity of interest is the Democratic **share of vote in each state**
- Unifies historical forecasts based on **structural variables** with state-level **poll data**
- In each state, voting preferences follow a **reverse random walk**: starting on election day, the estimated intentions evolve randomly going back in time

Bayesian Models - Linzer

$$\pi_{ij} = logit^{-1}(\beta_{ij} + \delta_j)$$

where π_{ij} is the share of voting preferences for state i and day j, β_{ij} represents the historical voting preferences in state i and δ_j is a national effect

To obtain an estimate for those days when no polls are available, two reverse random walk normal priors for β and δ

$$\beta_{i,j-1} \sim N(\beta_{i,j}, s^2_\beta) \qquad \delta_{j-1} \sim N(\delta_j, s^2_\delta)$$

Bayesian Models - Linzer

The historical forecasts h_i are obtained using the Time-for-Change model and are incorporated through a Normal prior for the final outcome β_{iJ}

$$\beta_{iJ} \sim N(logit(h_i), \sigma_i^2)$$

where $\tau_i = 1/\sigma_i^2$ is the precision and indicates the level of certainty on the historical forecasts, that is higher τ_i implies higher weight to historical prediction over new polling data

Bayesian Models - Linzer

The posterior probability the Democratic candidate wins in state i is calculated as the proportion of draws from π_{iJ} greater that 0.5.

In particular, when the election is soon estimates of π_{iJ} are based primarily on poll data, whereas if the election is farther ahead are driven by the historical prior.

4. Conclusions

Conclusions

- A Bayesian approach to produces **continuously revised forecasts** as new poll data is released
- **Comparing performances** of different models is difficult (different elections, different horizons, different purposes)
- In general, forecasts are accurate **within 2 months** before the election day and forecasting using both structural variables and poll data outperform others
- It is **still difficult** to produce timely and accurate forecasts
- **Problems** arise in forecasting accuracy and uncertainty for states that are polled few and in those days with no polls at all

Conclusions

- **Web data** as a source of spontaneous public opinions to solve lack of data issues (as *Rizk et al., 2023*)
- **Correlated vote intentions** across states (for example, if a candidate is performing bad in a state, this might indicate that he will also underperform in other states)

These factors may help to improve early forecast accuracy of the models

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Thank you!