

Election Forecasting with Online Polling Data

Evidence from Dalia Europulse Survey

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Outline

- 1. Intro to Election Forecasting: Methods**
- 2. State of the Art Polling**
- 3. Employing Dalia Data: Our Methodology**
- 4. Our Forecasts**
- 5. Take Aways**

Election Forecasting: Methods

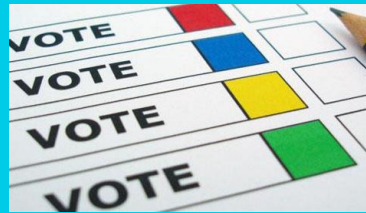
Fundamental Models

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

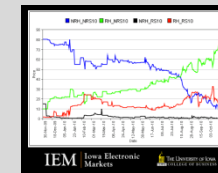
e.g. Party popularity

e.g. GDP

Polling / Surveys



Wisdom of the Crowd



Markets,
Competitions,
Aggregated
Forecasts

Digital Trace Models



Combining Forecasts

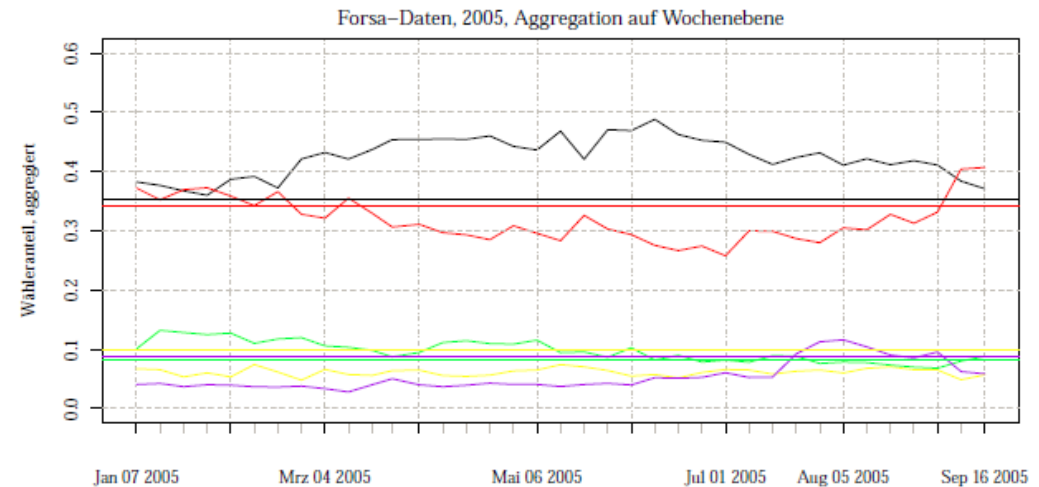
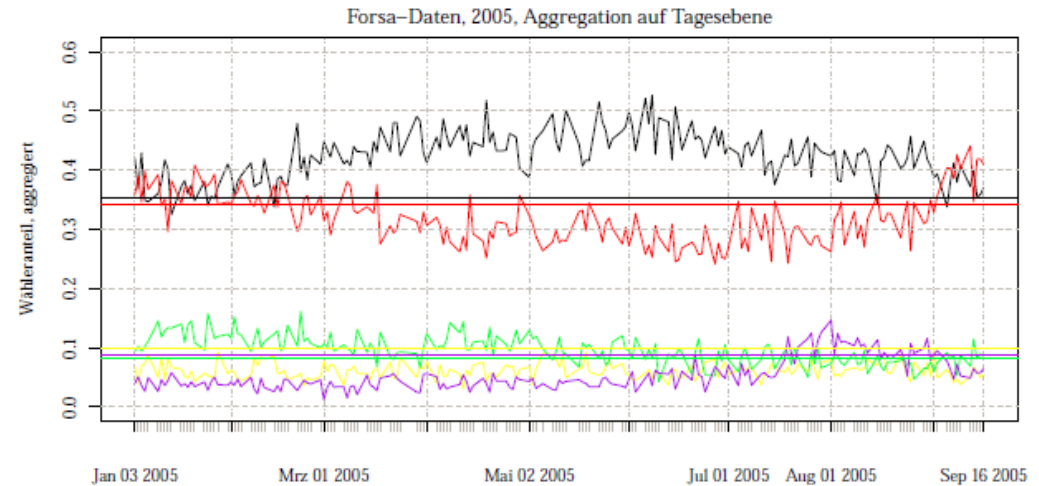
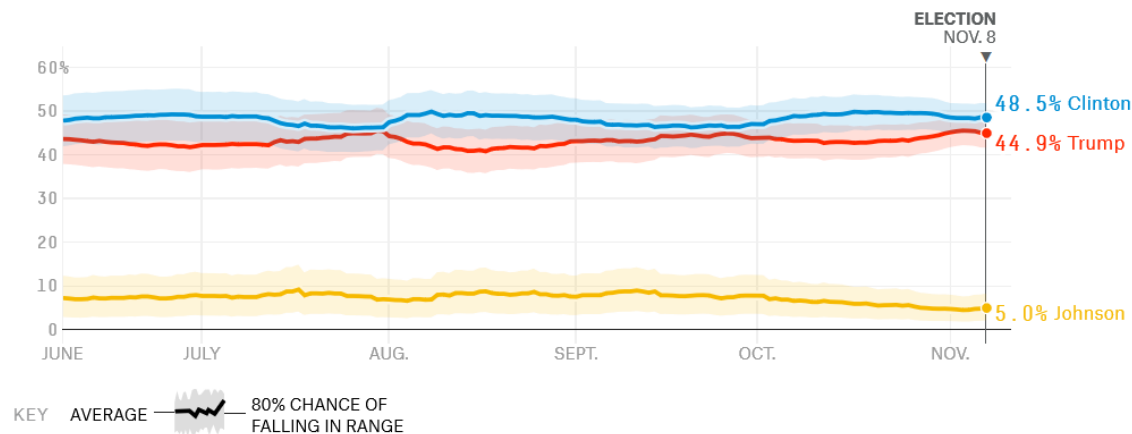


Hybrid Models



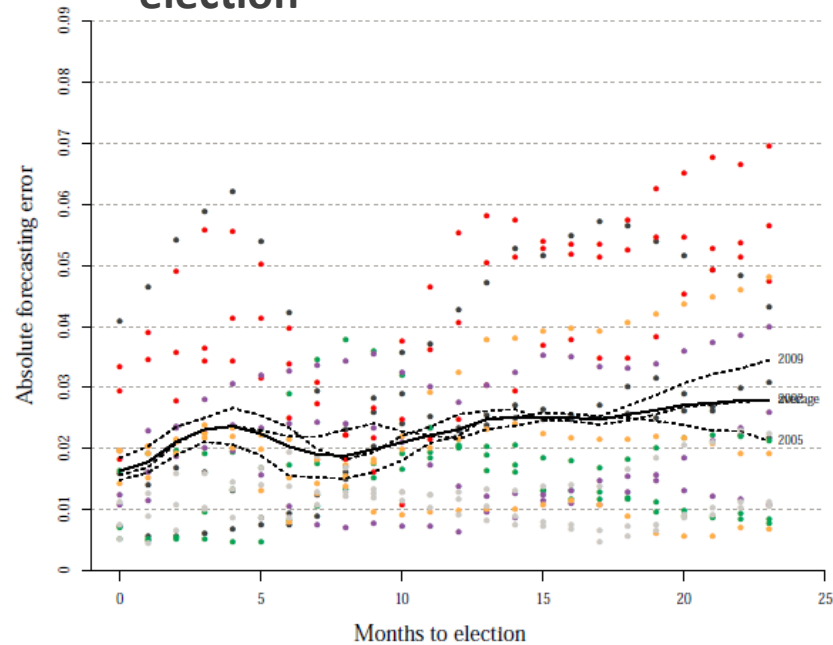
Polling: Extracting the signal

- Single polls can vary strongly
 - Noise due to simple sample variation
- **Uncertainty** often not represented
- Tendency to **horse race journalism**
 - Reporting any change of party support
 - Statistical standard errors are ignored



Polling: Accuracy and Confidence

- Generally: **Accuracy** increases as elections approach
- But: Campaign noise before elections
 - More accurate polls 8 months before actual election



- Most election polls are based on small samples (n=1000)
- Showing **robust change** in voter support is difficult

$$\hat{v}_p \pm 1.96 \sqrt{\frac{\hat{v}_p(1-\hat{v}_p)}{n}}$$

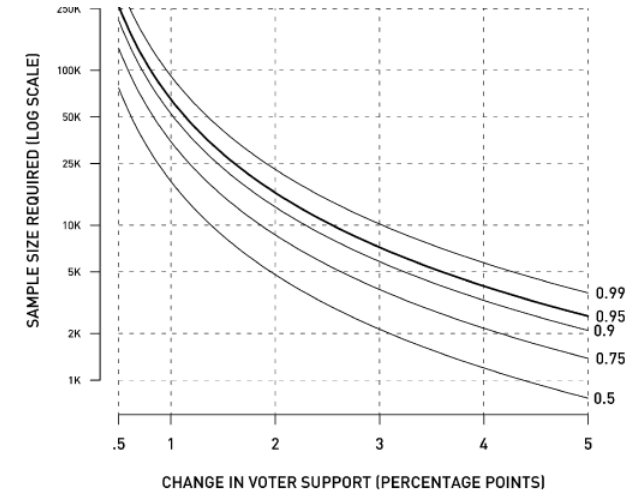
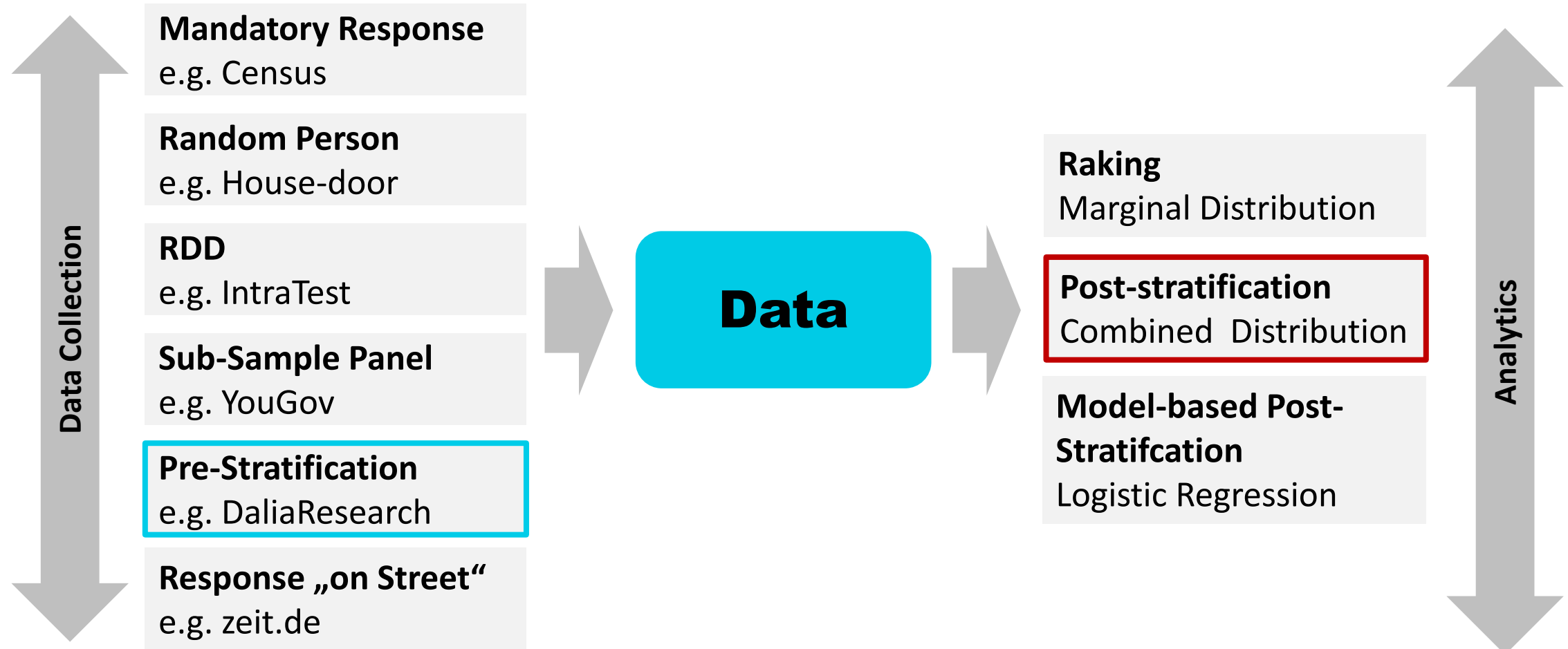


Figure 1. Sample size requirements. *Notes:* Each curve shows the sample size (vertical axis, log scale) required to detect the indicated change in support (horizontal axis, assuming a baseline level of 50%), with probability given by the label next to each line. In each instance it is assumed that the researcher's decision problem is whether to reject the null hypothesis of no change in favour of a two-sided, alternative hypothesis, using a 95% confidence level or better (ie a p -value of 0.05).

Polling: Collection vs. Analytics



Adjusting Europulse Data: Methodology

Data

Surveys:

Europulse Wave December 2016 and March 2017

Variables: last vote, next vote

Post-stratification: two variations

1. **Census 2011** with gender, age and religion
2. **Exit-polls** with age, gender and vote (combined probabilities)

Benchmark data:

Aggregated polls from **Sueddeutsche**

Combined probabilities: explained

	Catholic	Protestant	Total
Men	?	?	7
Women	?	?	13
Total	17	3	20

	Catholic	Protestant	Total
Men	6	1	Σ
Women	11	2	Σ
Total	Σ	Σ	Σ

Adjusting Europulse Data: Methodology

Post-stratification approach

- Combined distribution of demographics: age, gender, education, rural/urban, religion etc...
- Weights for every cluster: e.g. Women above 60 from rural settlement
- 4% of population, but only 2% in sample
→ Weight: 2

General problems of post-stratification

Exponential growth of clusters:

1. Small cluster ($n < 30$) => large errors
2. Empty cluster => no weights

⇒ Ad hoc solution: Combining categories (e.g. merge age categories)

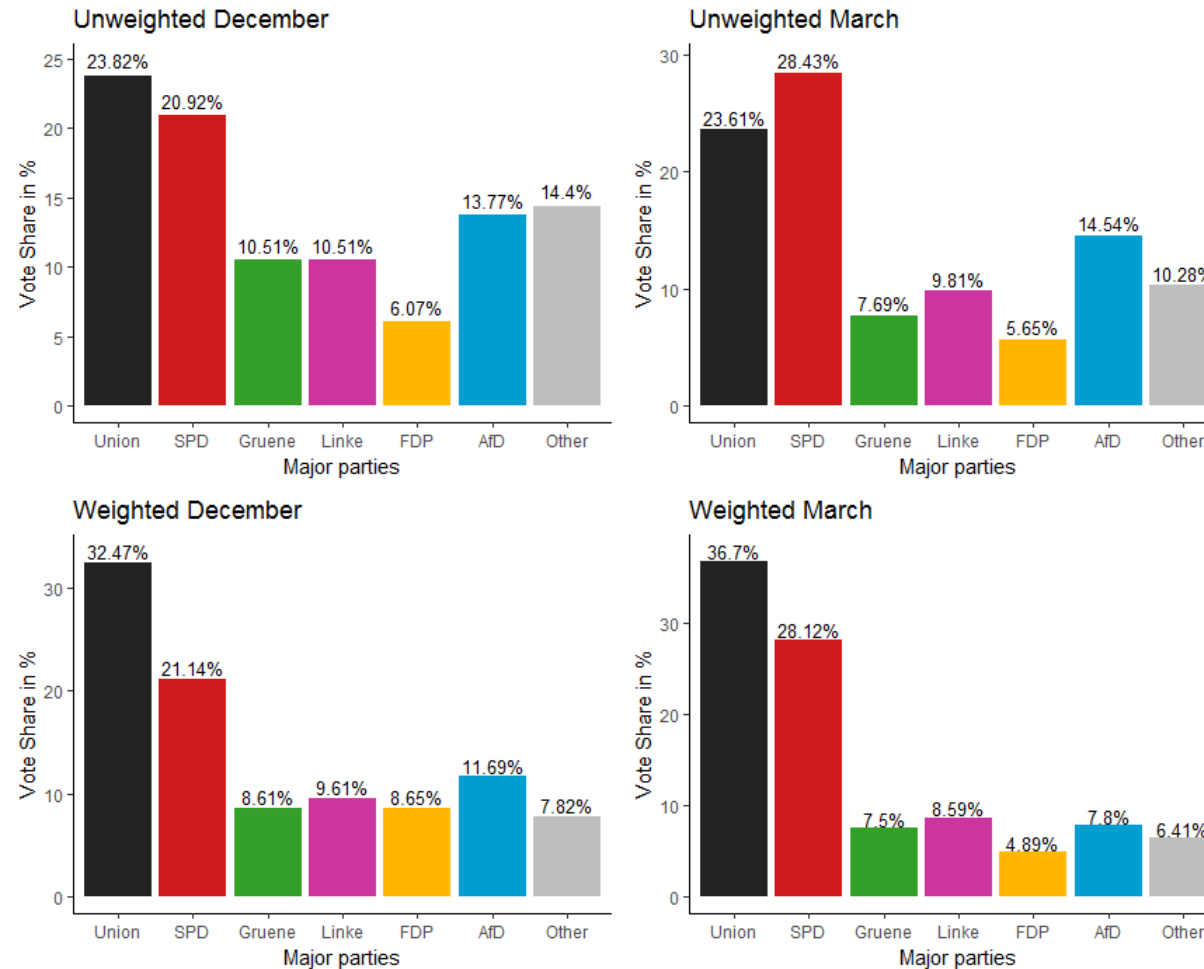
Weights Calculation

DALIA POLL	SPD	CDU	Total
Men	2	8	
Women	6	5	
Total			

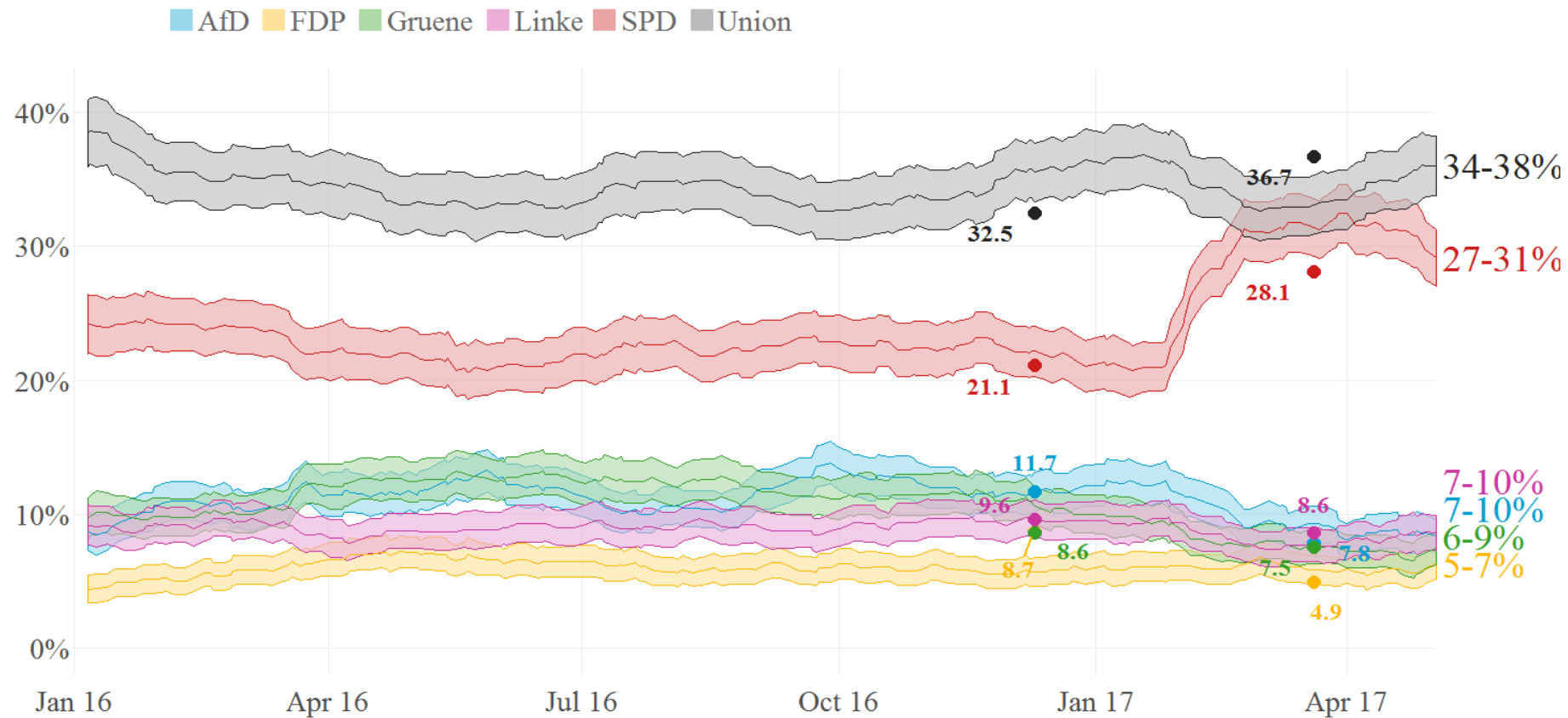
EXIT POLL	SPD	CDU	Total
Men	4	6	
Women	4	7	
Total			

Weight: MEN+SPD = 2

Adjusting Europulse Data: Results



Adjusting Europulse Data: Results



=> Post-stratification with publicly available exit polls lead to quite good results compared to benchmark data

Adjusting Europulse Data: Take aways

1. Pre-stratification not sufficient for election polling (likely voter)

2. Post-stratification with past-vote is promising

3. No improvements from census-only post-stratification

4. Further fine-tuning: Disaggregated data + more waves

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Q&A

What can be the role of election forecasting for Dalia?

APPENDIX

Digital Trace Models



Twitter:

- **Idea:** # of mentioning
- Some successes (Tumasjan et al. 2010)
- But:
 - Not replicable (Jungherr et al. 2012)
 - Twitter usage very low, in particular in Germany



Wikipedia

- **Idea:** Information seeking before election
 - Tested by Yasseri and Bright (2016) for European Elections
- Little insight into absolute vote outcomes
- Good information about changes in both overall turnout at elections



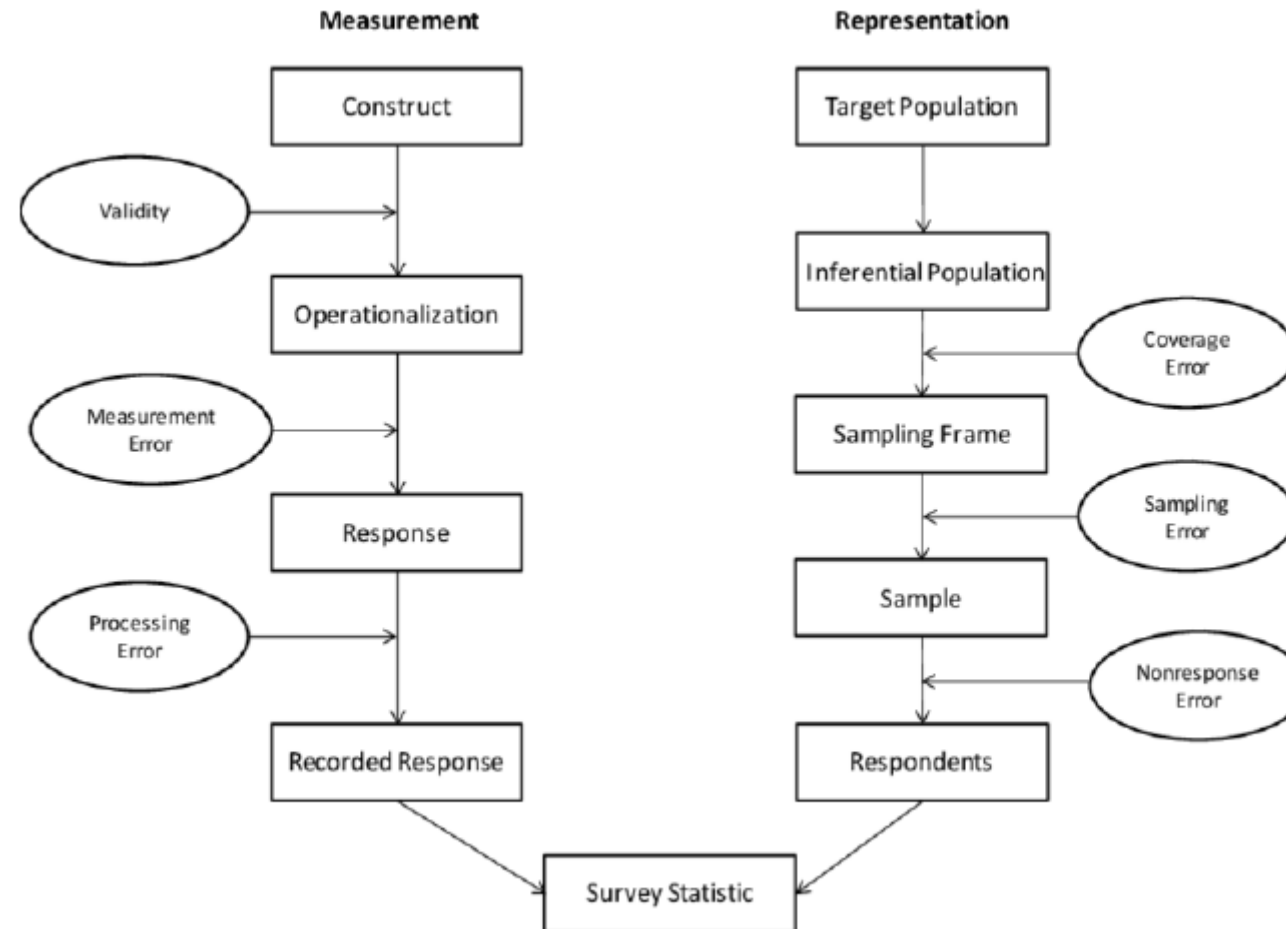
Google Search

- **Idea:** Compare # of searches of parties / candidates
- Result: Good measure of public attention

Fields of applications

- Influenza incidence
 - E.g. Google Flu Trends
 - But relation broke down
- Product sales
 - E.g. Books, films
- Stock markets
 - Online follows market and not the otherway
- Elections

Sources of Error

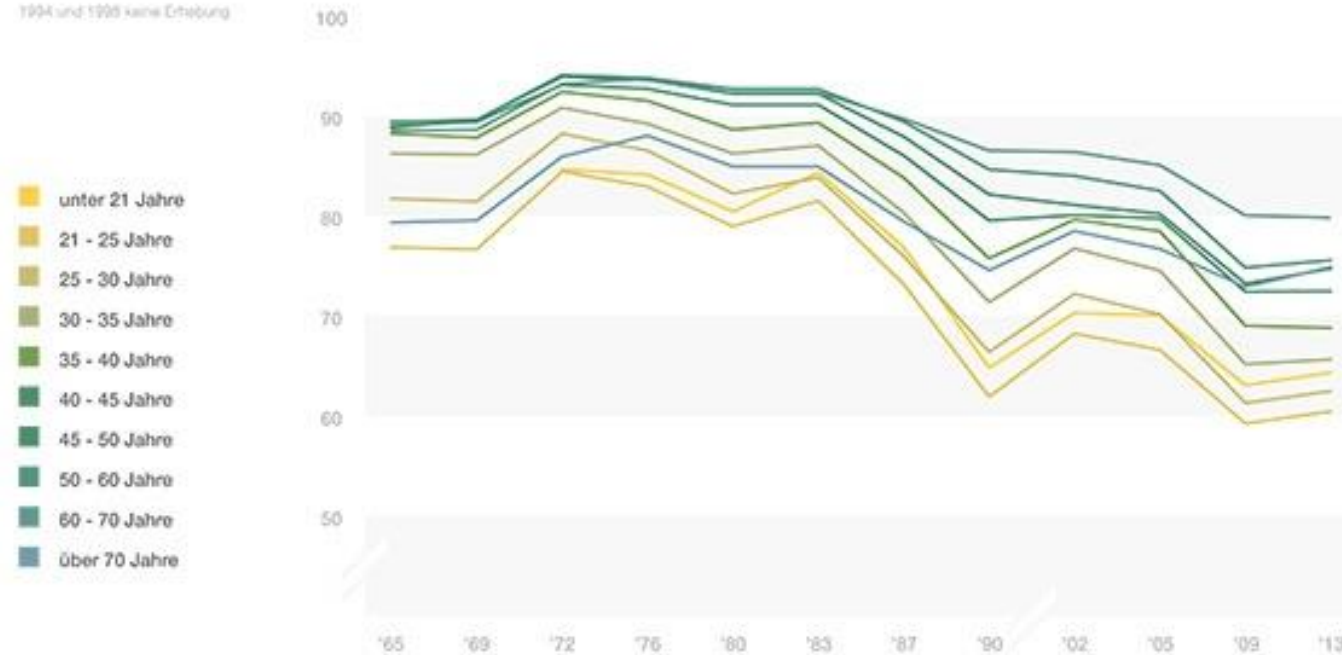


Turnout

■ Wahlbeteiligung nach Altersgruppen

In Prozent, Bundestagswahlen 1965 bis 2013

1994 und 1998 keine Erhebung



Quelle: Der Bundeswahlleiter
Lizenz: Creative Commons by-nc-nd/3.0/de
Bundeszentrale für politische Bildung, 2014, www.bpb.de



Statistical Models

Example

Kanzlermodell by [Gschwend und Norpoth \(2010\)](#)

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

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

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 Convention Bump and Economy	50.7% Labor Day/Economy	69%	60
		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 Jérôme-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