

What Citizens Want from the Economy

Determinants and Predictability of  
Economic Evaluations

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# Goal: Uncover which economic outcomes citizens value

- What drives beliefs about state of the economy?  
Many (too many?) possibilities?
  - GDP growth
  - How easy/hard it is to find a job? How many jobs are created?
- General problem/blessing: large number of covariates
- **Claim:** approaches from machine learning can reliably identify the attributes of the economy that drive subjective economic sentiment

# Summary

- RQ: When is the economy doing “well enough” according to citizens?
  - When the labor market indicators are favorable
  - Methodological contribution: characterize uncertainty around split points
- RQ2: How serious are partisan biases of US respondents’ economic evaluations?

# Two related tasks

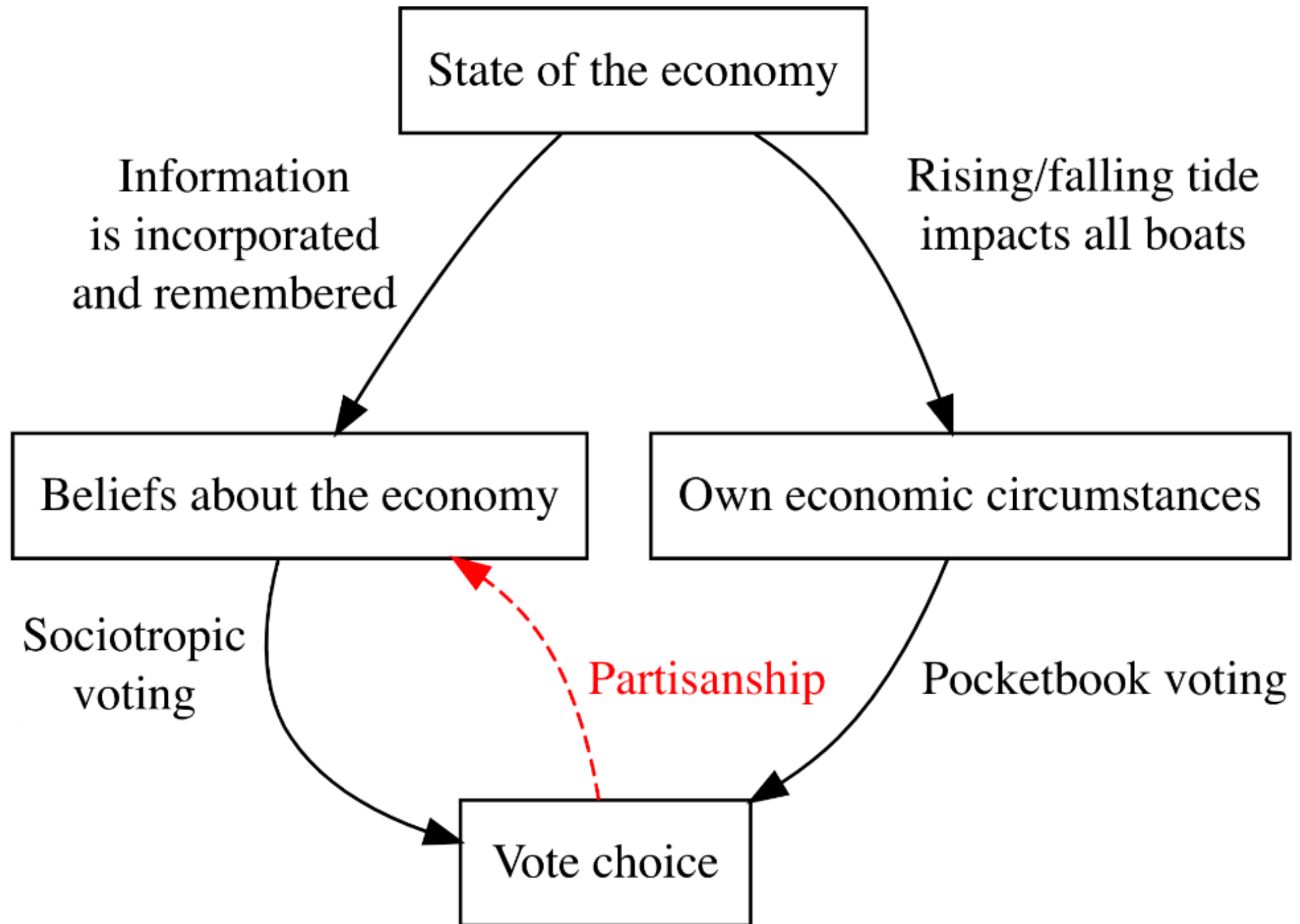
- **Forecast:** How many people do we expect to be satisfied with state of the economy in country X, given certain macroeconomic conditions?
- **Parameter estimation:** Under what conditions are most people likely to be unhappy about the state of the economy?

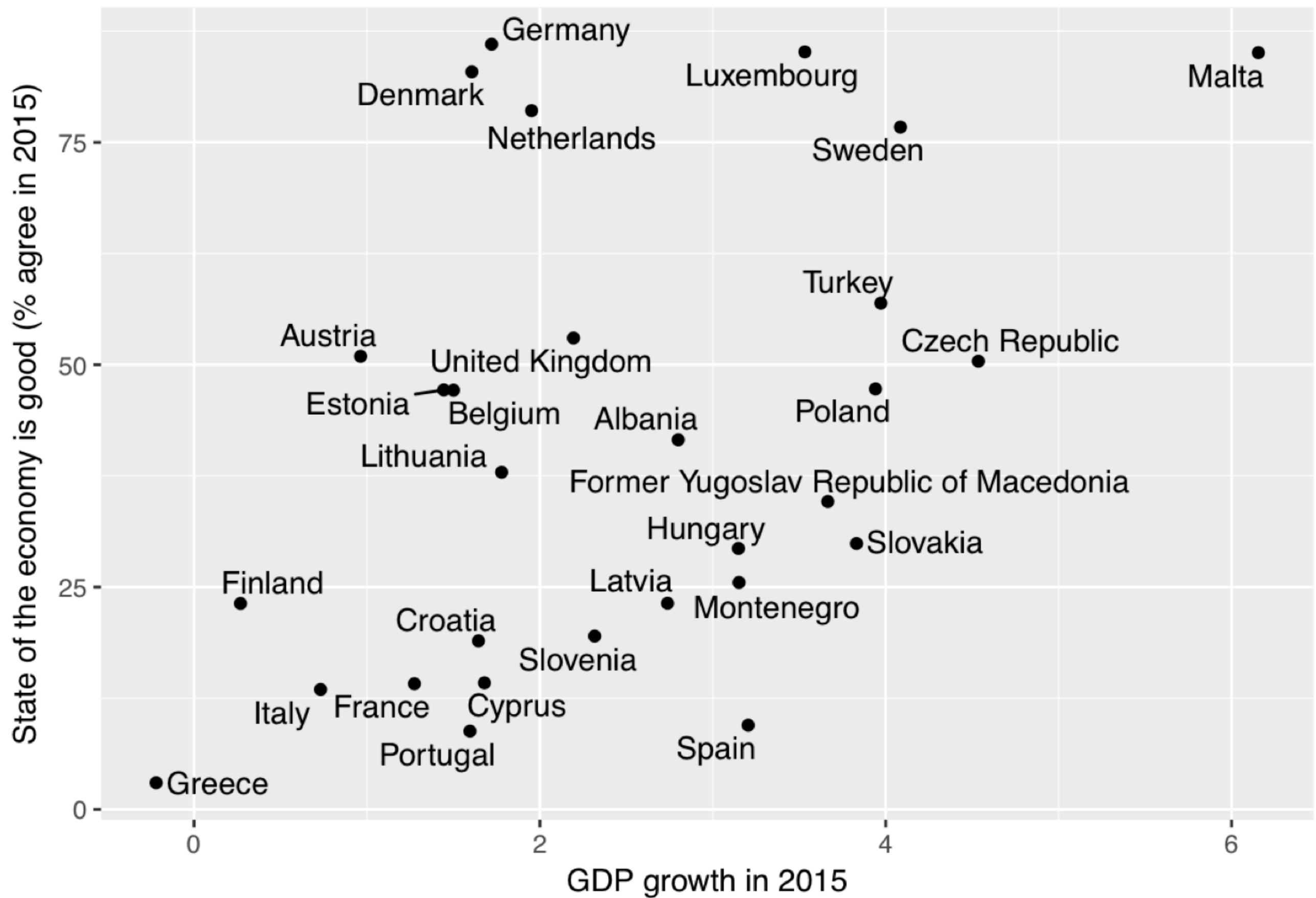
# Data & Methods

- Eurobarometer/Gallup/Pew data. How would you judge current economic conditions?
- **Outcome:** Proportion of respondents evaluating the economy positively
- Common approach: add “plausible” covariates into a long regression
- Alternative: disciplined variable selection
  - Allows for search over a rich set of variables and functional forms
  - Let data decide how to make the bias–variance trade-off *Kleinberg et al. (2015)*

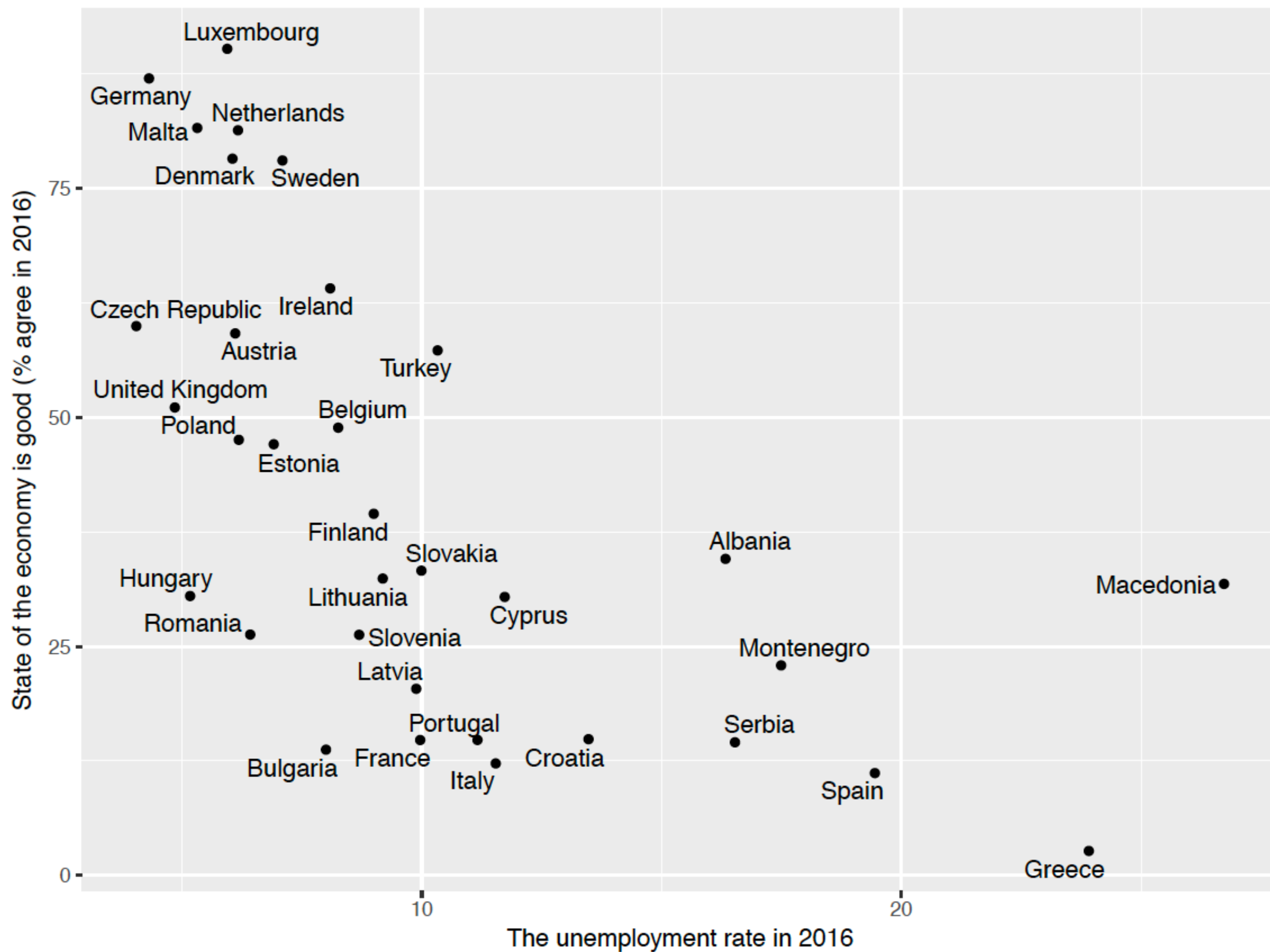
# Plausible feature space

- GDP growth (annual %)
- GDP per capita, PPP (current international \$)
- Inflation
- Unemployment rate
- Personal remittances, received (% of GDP)
- Government expenditures (% of GDP)
- General government final consumption expenditure (% of GDP)
- Exports of goods and services (% of GDP)
- Gross fixed capital formation (annual % growth)
- Trade (% of GDP)
- Agriculture, forestry, and fishing, value added (% of GDP)
- Manufacturing, value added (% of GDP)
- Industry (including construction), value added (% of GDP)
- Industry (including construction), value added (annual % growth)
- **And 70+ other variables**









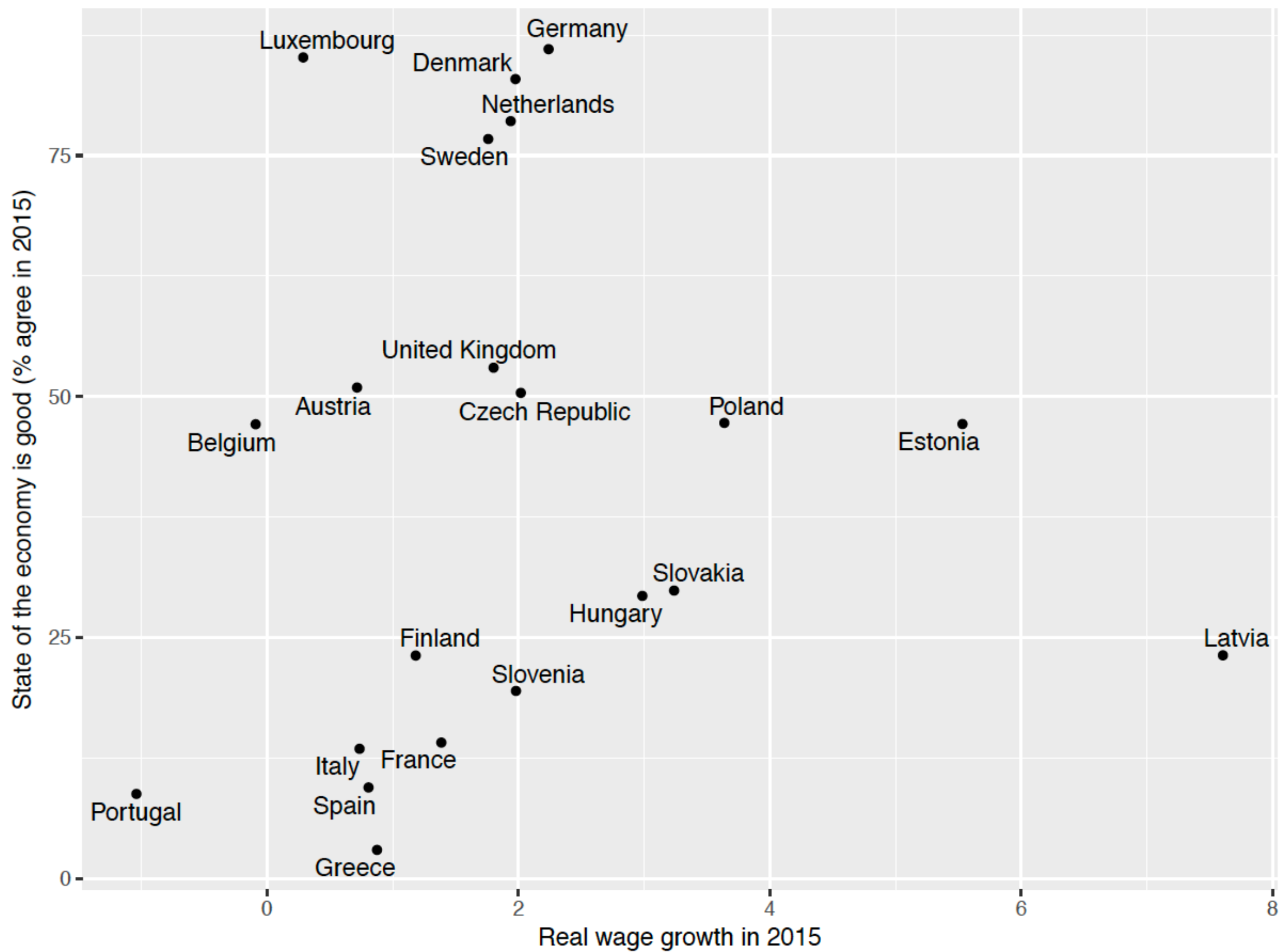
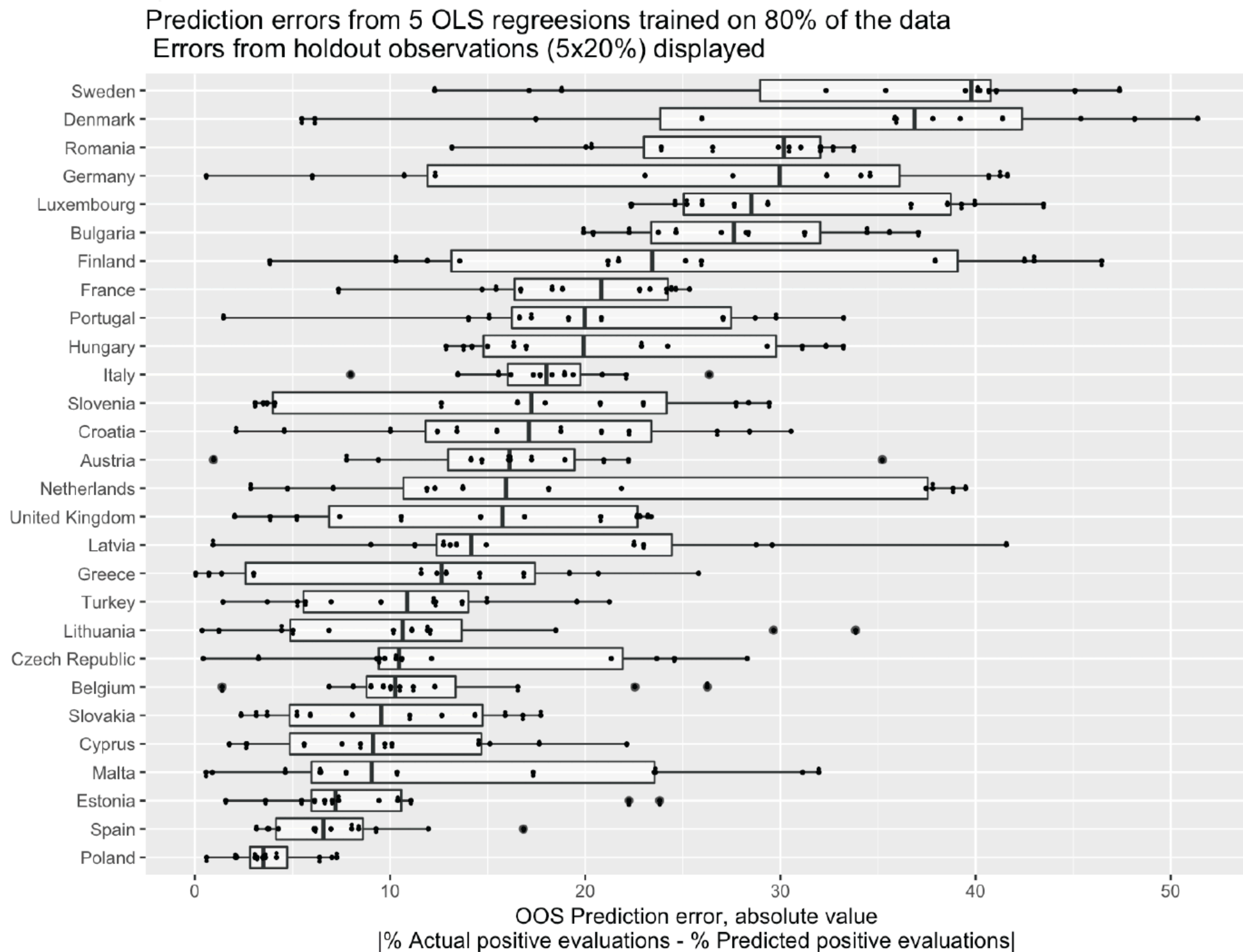


Figure 2. Out-of-sample residuals. Data: Economic sentiment in the EU & neighboring countries, 2005-2016.



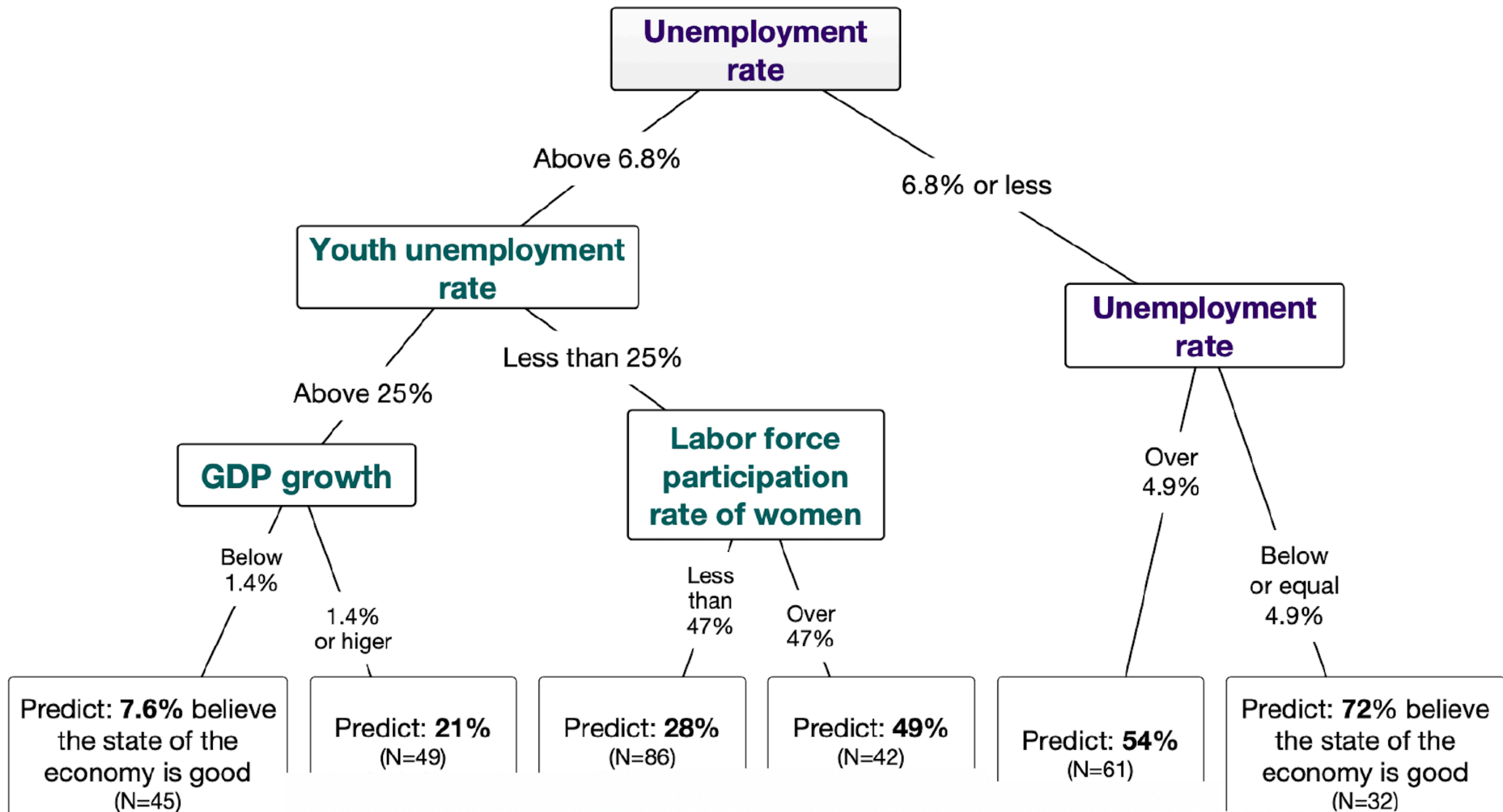
# Search for best predictors

## Regression trees

- Sequentially partition the covariate space
- Pick an optimal split of the data to minimize deviance (squared residuals)
- Check all variables but only pick the most diagnostic one at each step
- Typically keep going until a large tree is built, then prune

## Random forest

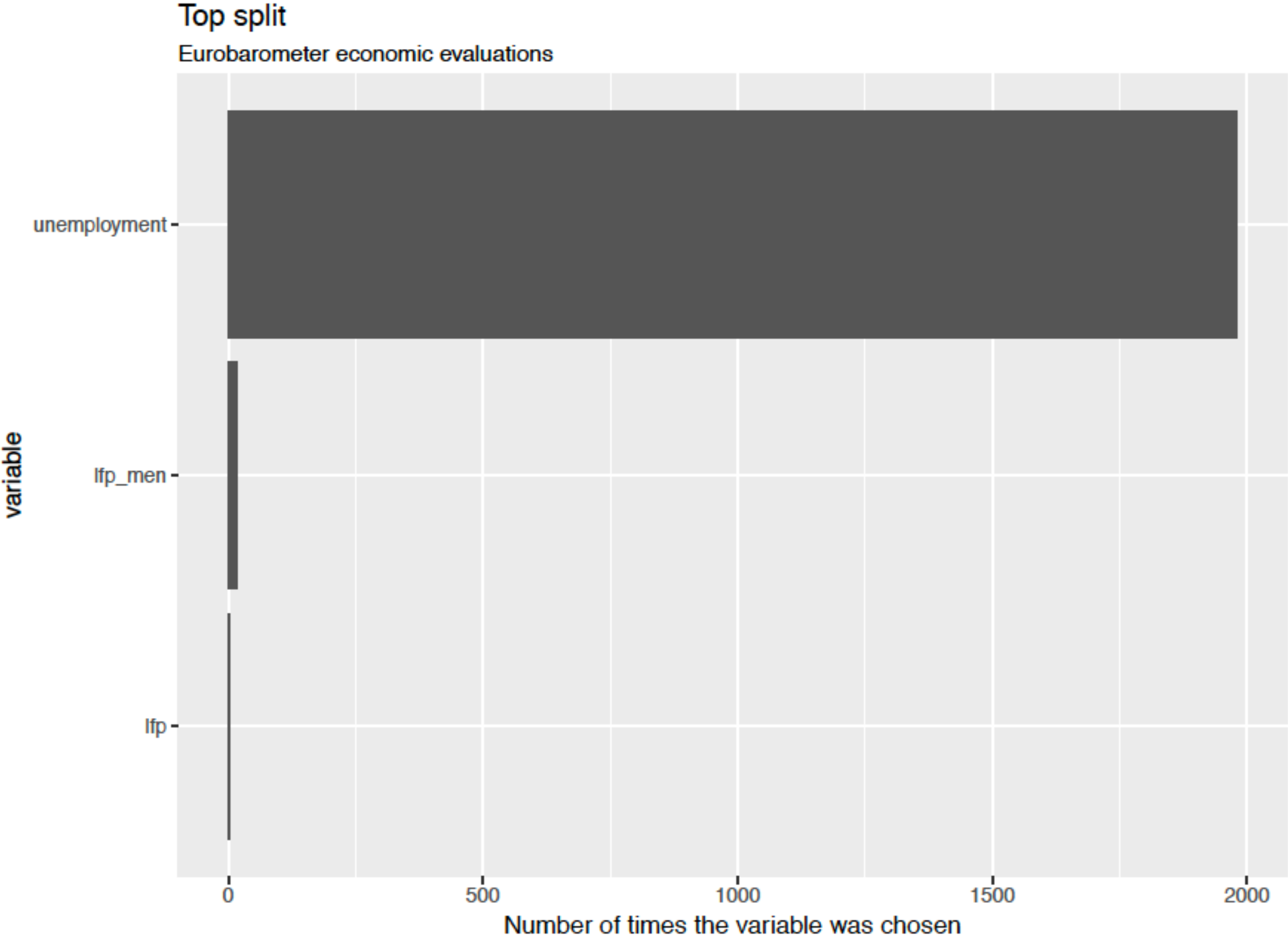
- Randomize which variables are available for splitting at each step
- Grow 1000 trees. Let each tree make a prediction.



# Questions

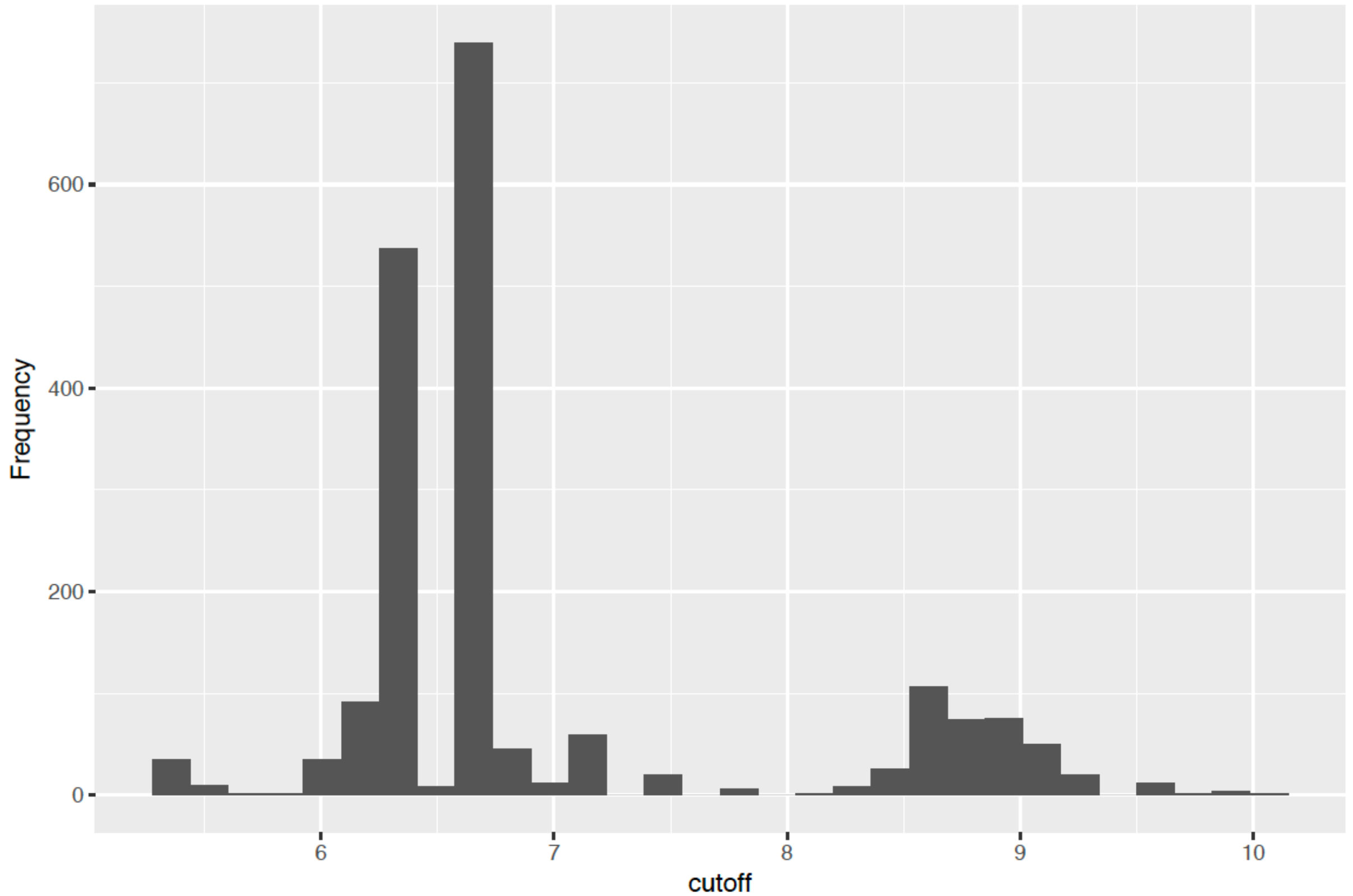
- How much should we trust the splitting procedure to reveal the most important variable?
- How fragile is the threshold value?
- Are simple prediction rules better at predicting economic sentiment than linear models?

# Distribution of top splits



# Distribution of unemployment rate cutoffs

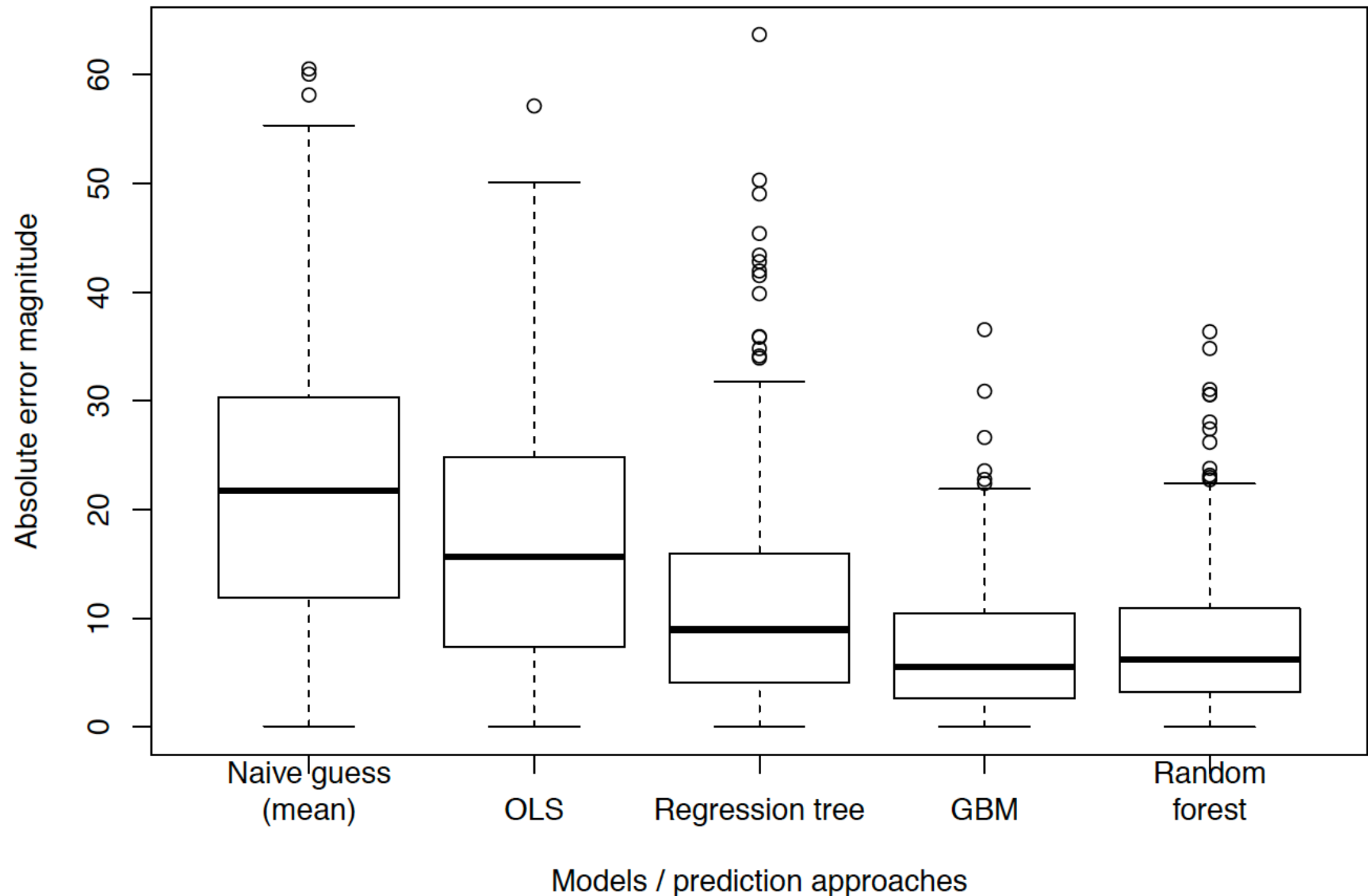
Thresholds for regression trees from random subsamples



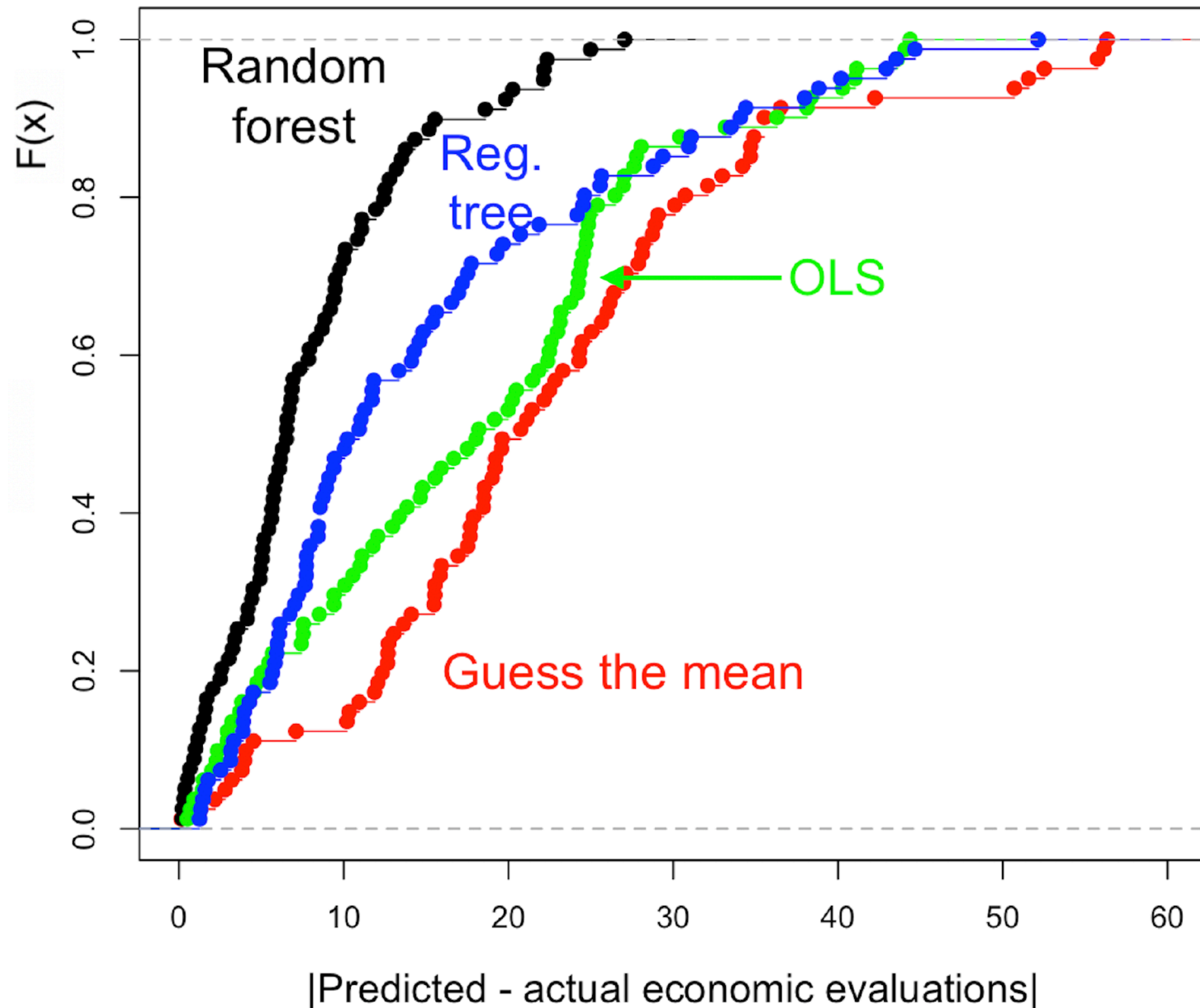


Out-of-sample performance of four modeling approaches relative to guessing the global mean (as a benchmark)

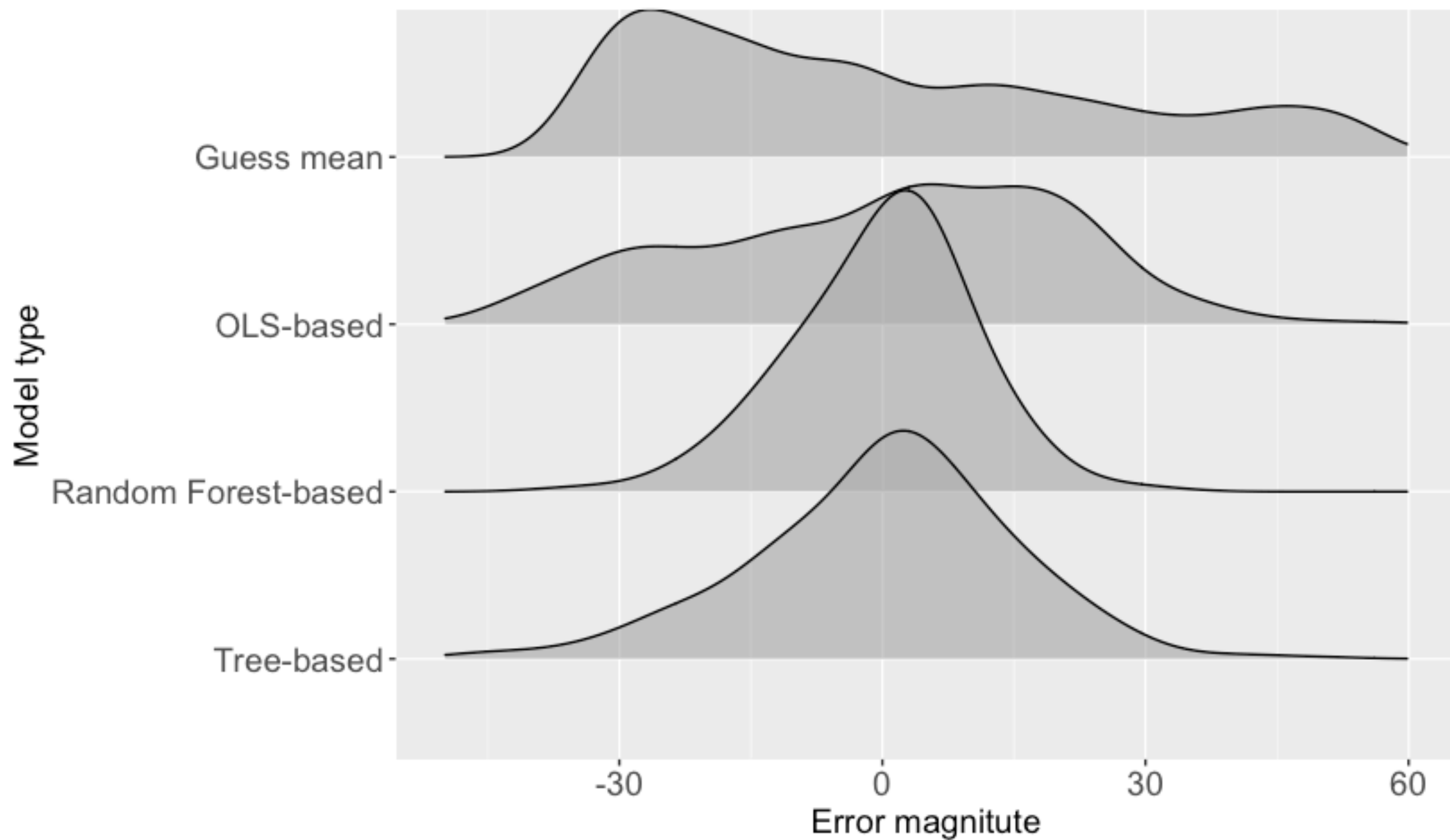
**Absolute errors based on 5 approaches**



Cumulative distributions of OOS absolute prediction errors obtained via RF, RT, OLS and guessing the mean



Comparison of OOS prediction errors by model type



# Midpoint

- Uncovered informative indicators with cross-national data
- Non-linear models perform better
- **Next:** Evidence from the U.S.

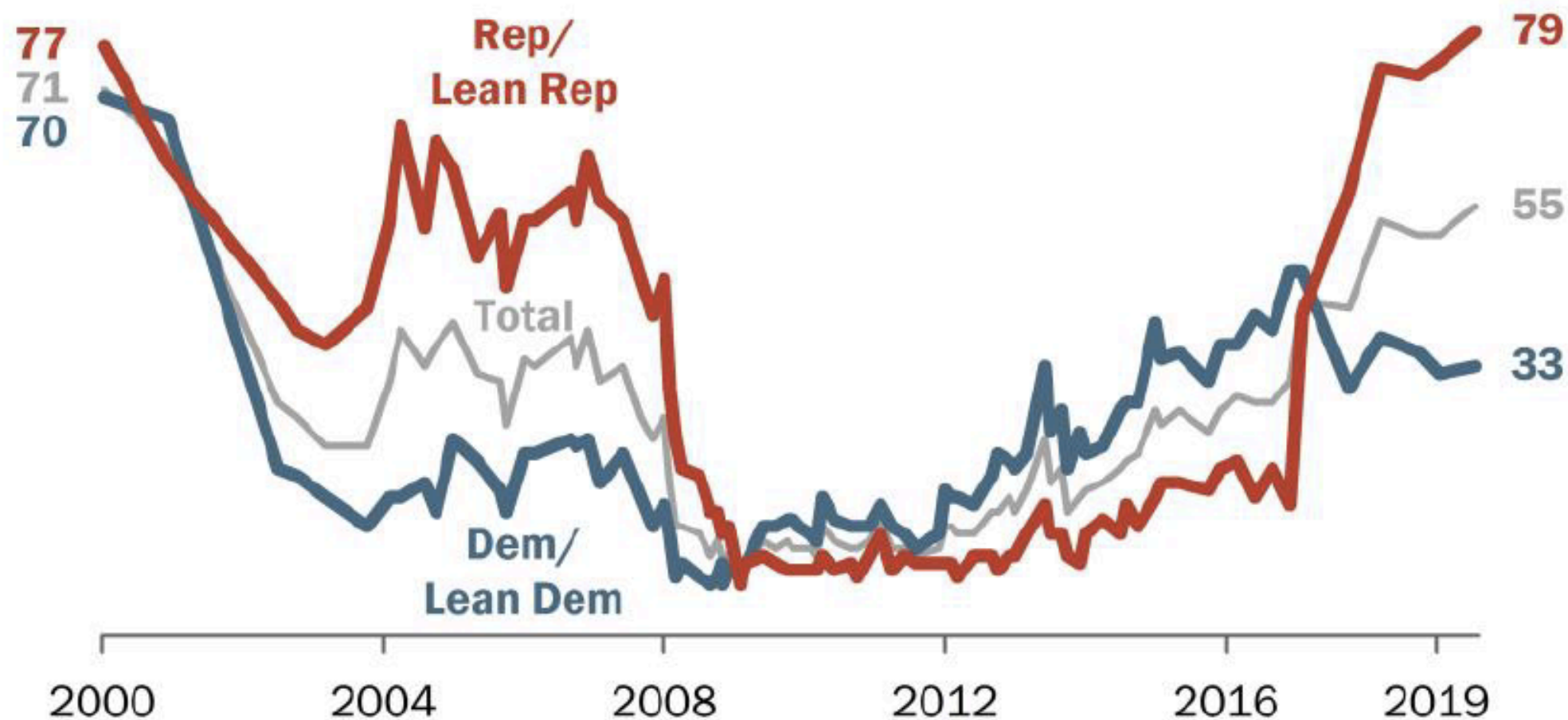
# Measurement challenge: misreporting and inattention

- Evidence of partisan biases: Main and Sufi (2017)
- Possibility: Economic evaluations are really measuring political opinions
- H: Only some citizens (non-partisans) are actually evaluating the economy
- H: Only in some (non-polarized) countries can we gather meaningful data on economic sentiment

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## Since Trump took office, positive economic views have surged among Republicans, sagged among Democrats

*% who rate national economic conditions as excellent or good*



Source: Survey of U.S. adults conducted July 10-15, 2019.

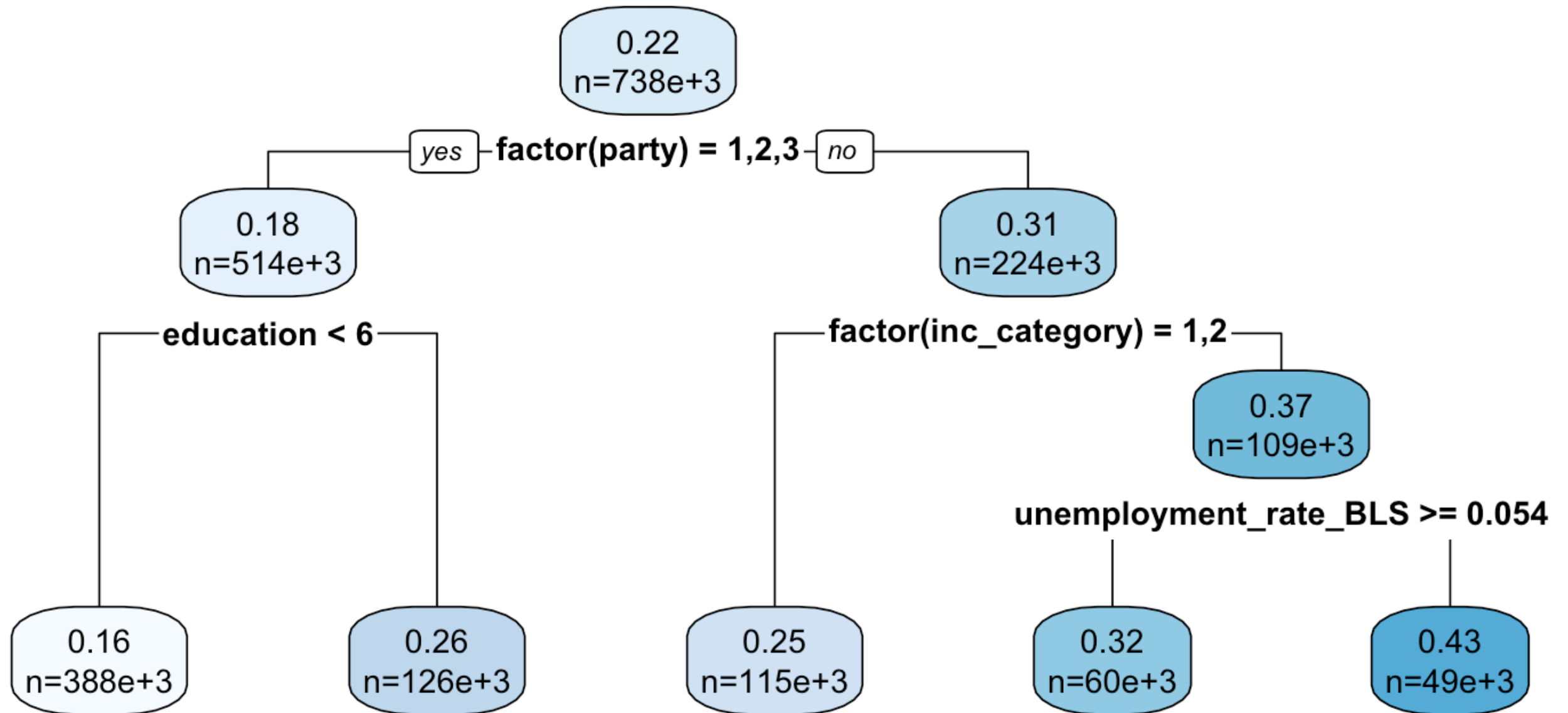
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# Individual-level analyses

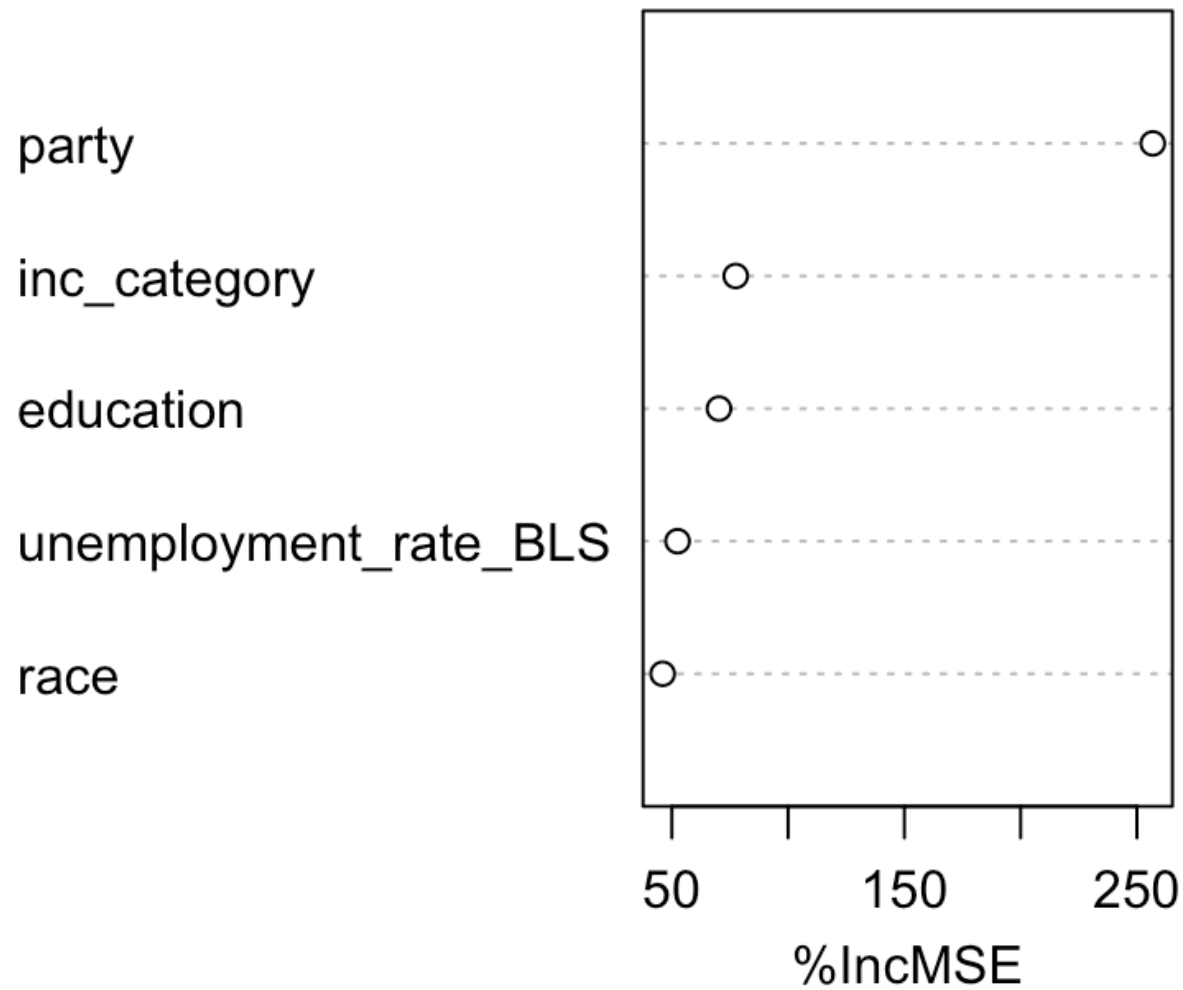
- Data: Gallup US daily polls. Feb. 2013 – Oct. 2016. N=733,343 (488,932 in the full model)
- Respondents' gender, income, race, age, education, religion, union status, marital status, type of work, party ID, ZIP/MPSA/county identifiers
- Merged in: unemployment rate (county), state-level GDP growth and LFP

## Gallup, individual-level

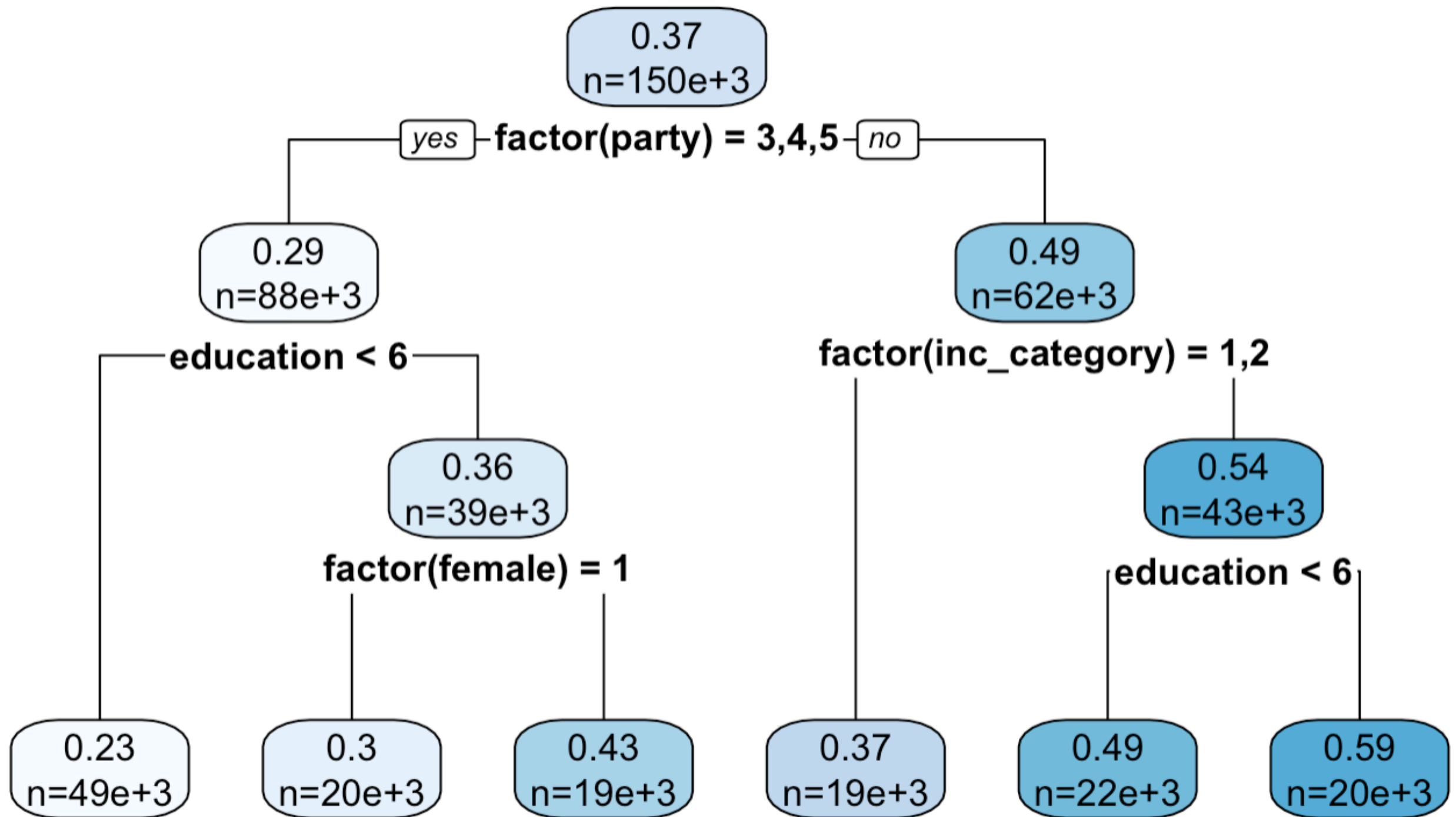




# Variable importance



## Gallup, Feb.-Dec. 2017, individual-level



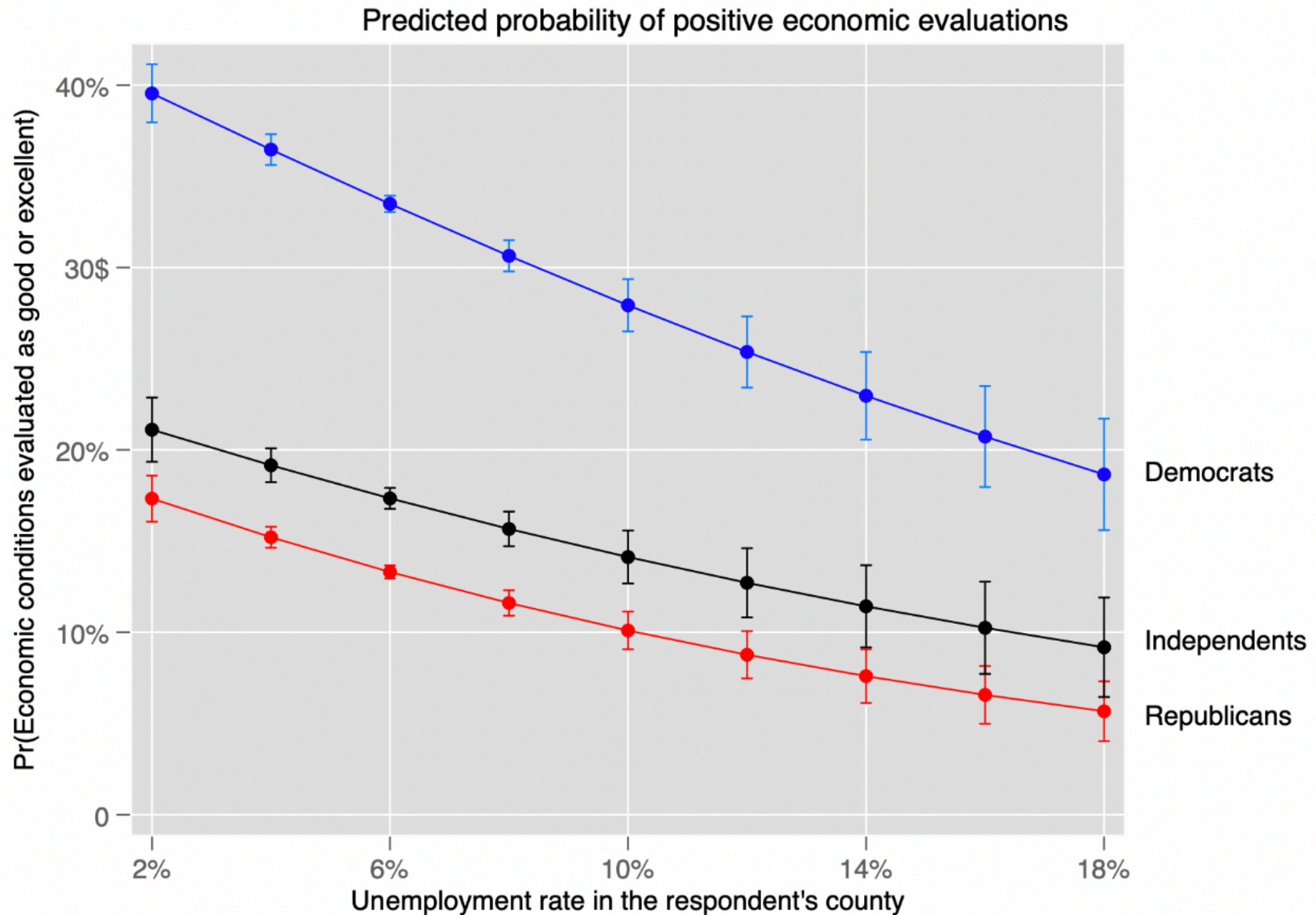
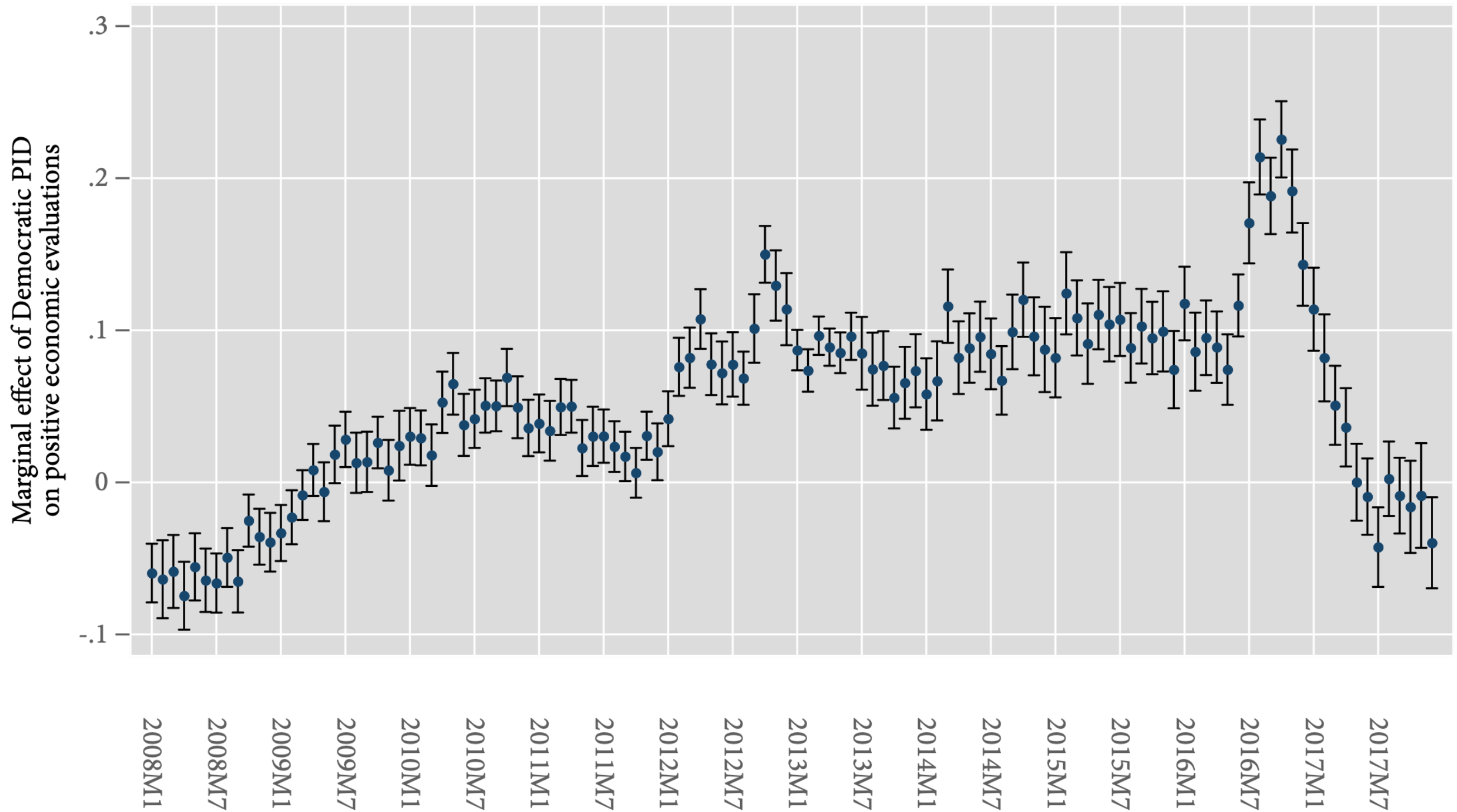


Figure 6: Predicted probability of positive economic evaluations by partisanship and by local economic conditions are based on a logistic regression where economic evaluations (=1 if positive) are regressed on local unemployment rate, and the labor force participation rate interacted with the party ID of each respondent. N = 236,915.

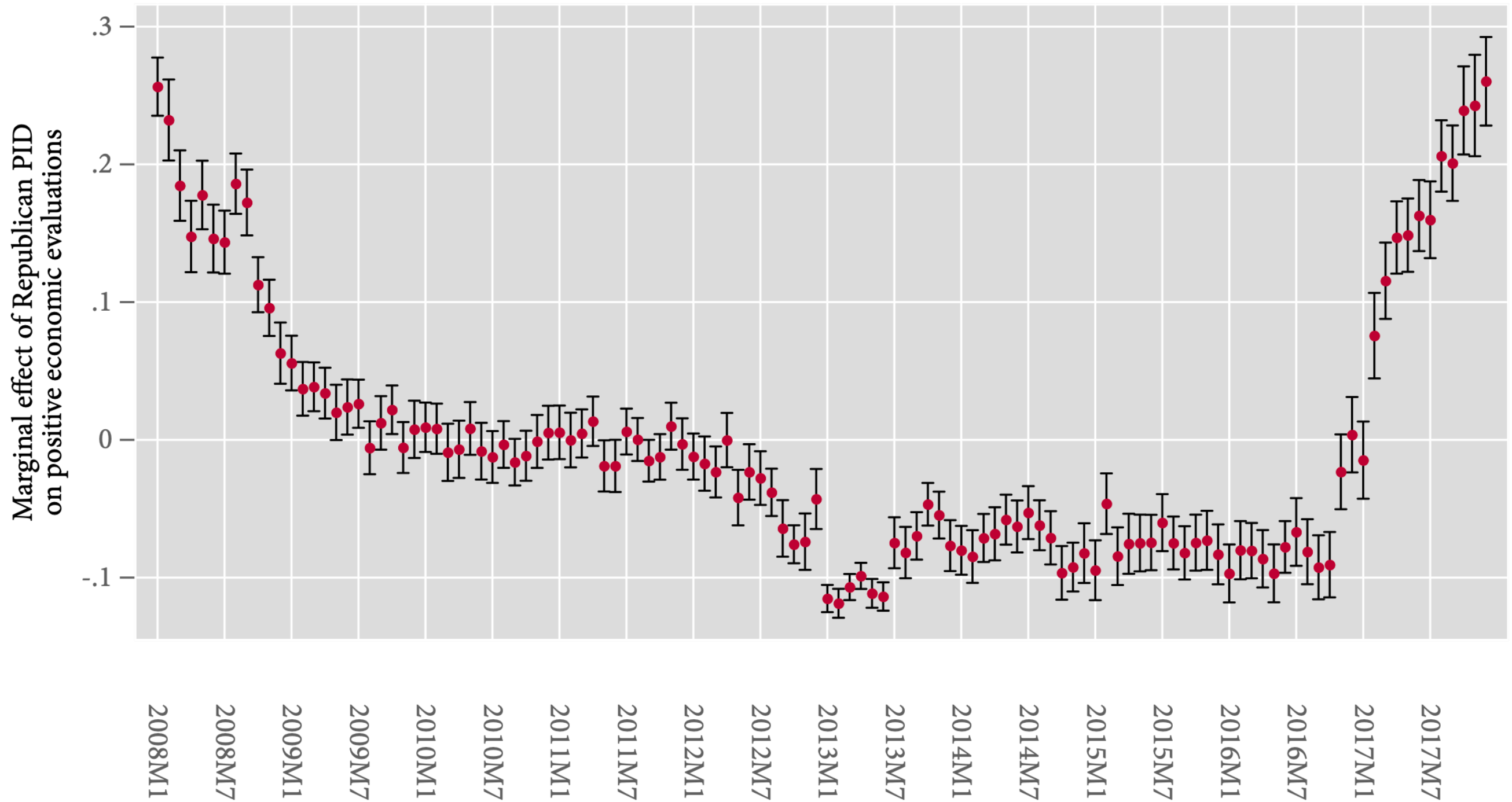
# The association between Democratic PID and positive economic evaluations (Conditioning on local unemployment and respondents' demographics)



N = 1472684 respondents

# The association between Republican PID and positive economic evaluations (Conditioning on local unemployment and respondents' demographics)

Results from 120 regressions



N = 1472684 respondents

# Summary of results

- Across-party comparisons: evidence of bias
- Within-party comparisons suggest local economic conditions matter
- Prelim. evidence: local economy matters less over time

# Conclusion

- Objective economic indicators and citizens' subjective economic evaluations are linked; voters notice the reality around them
- Economic variables interact and they do not map into perceptions linearly
- Some rules of thumb work well



# Benefits of tree-based methods

- Identification of interactions
- Superior OOS predictions
- Uncover key predictors
- Theoretically interesting parameters