

# DIY forecasting

## judgment, models & judgmental model selection

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a joint work with

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# Forecasting and ancient Greece

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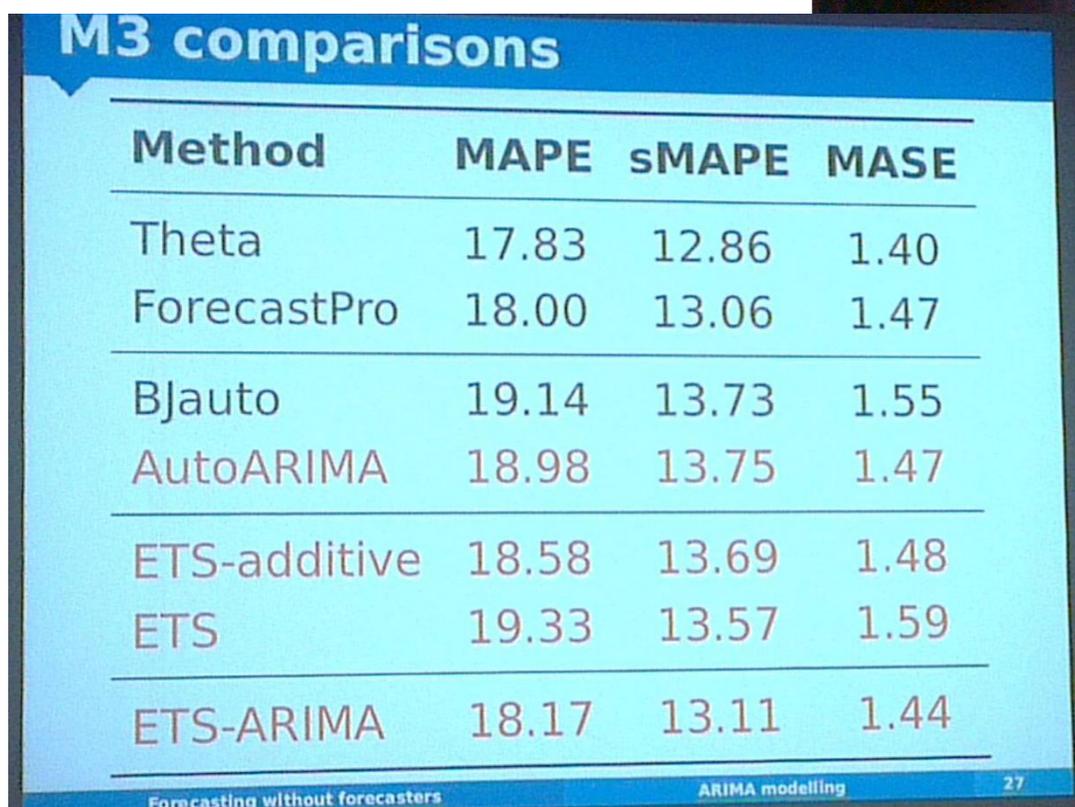


Pythia: the Oracle of Delphi  
(established in the 8th century BC)



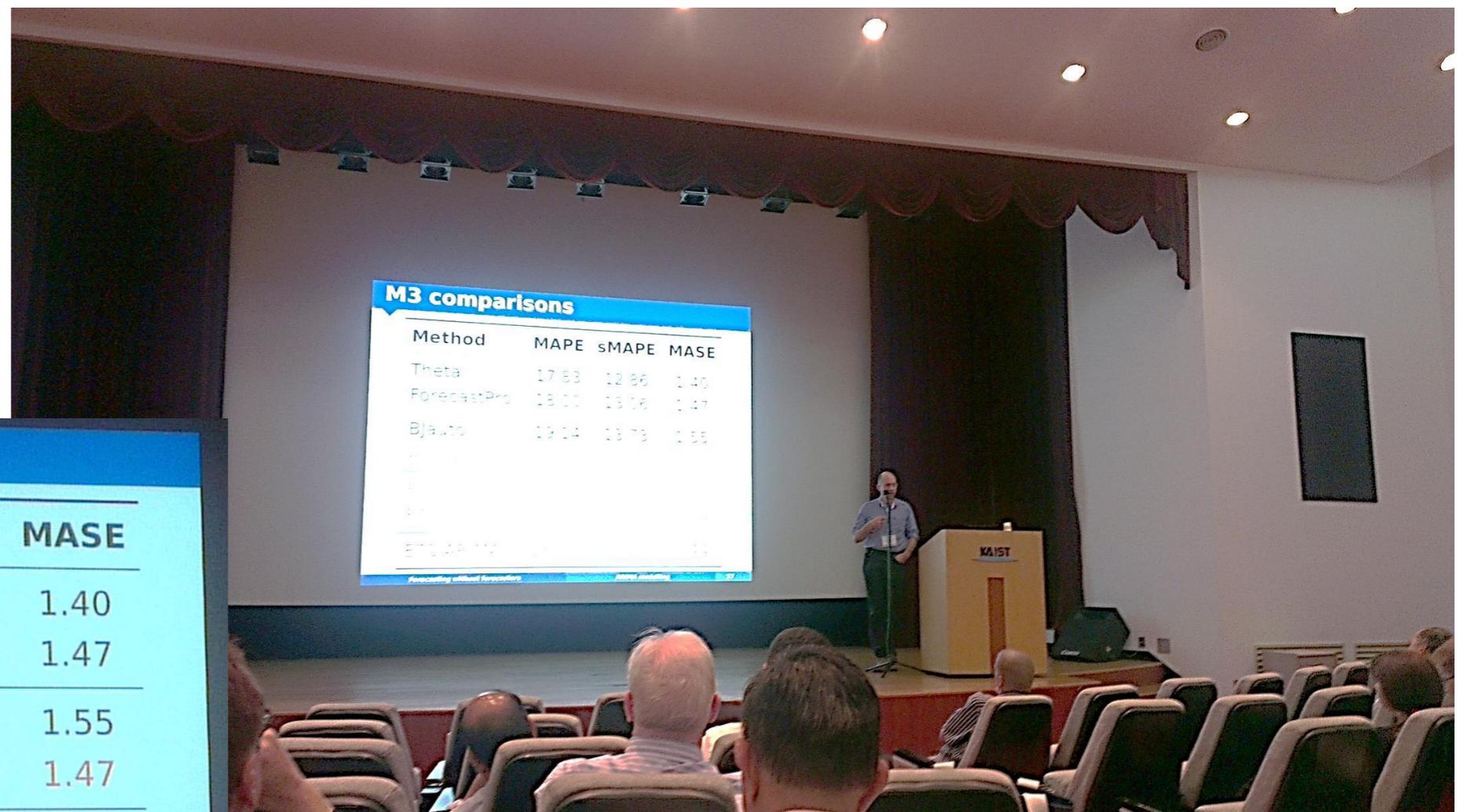
# Forecasting without forecasters?

Rob J. Hyndman (2013) "Forecasting without forecasters"  
Keynote Speech at the ISF2013

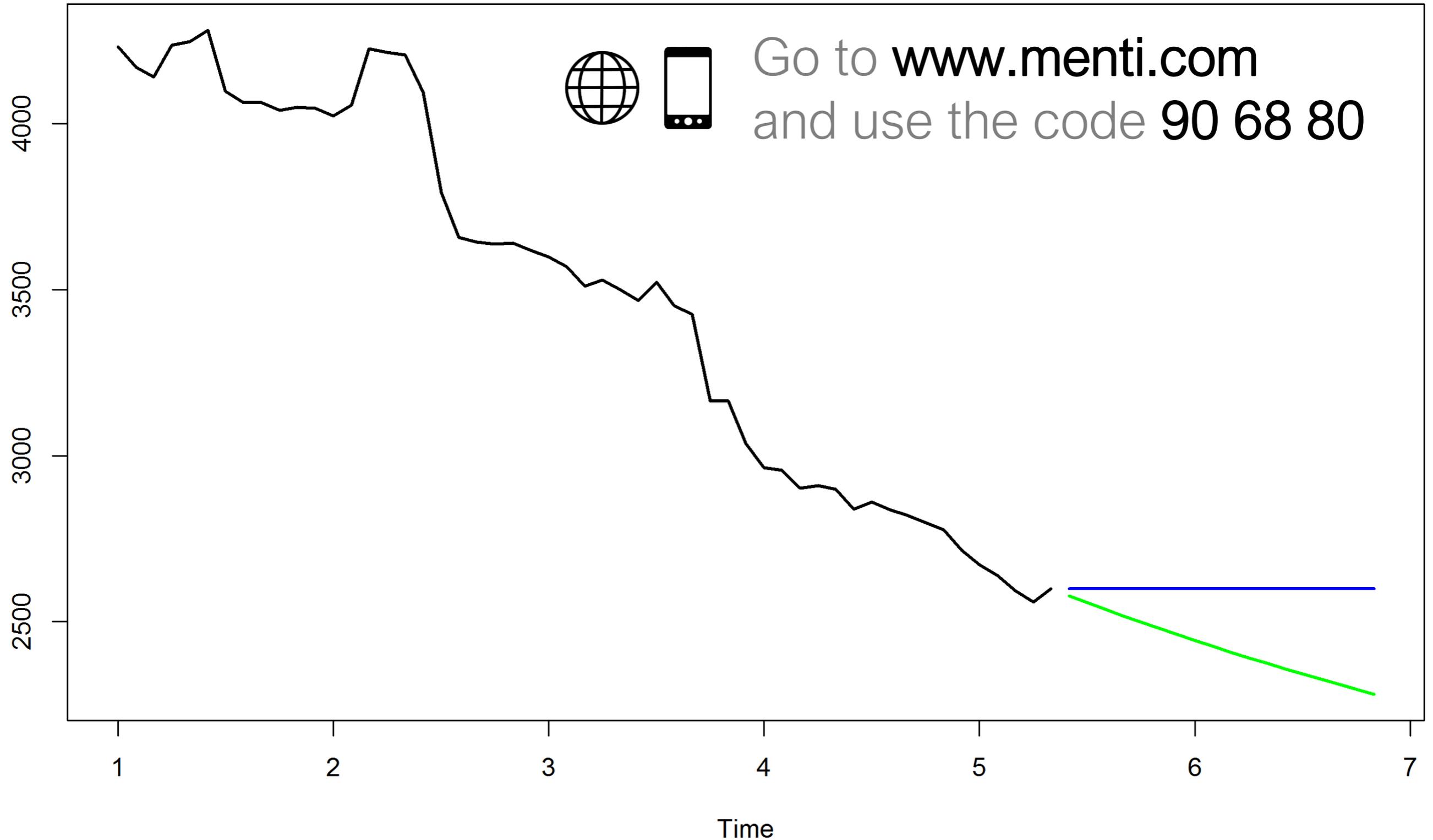


Method	MAPE	sMAPE	MASE
Theta	17.83	12.86	1.40
ForecastPro	18.00	13.06	1.47
Bjauto	19.14	13.73	1.55
AutoARIMA	18.98	13.75	1.47
ETS-additive	18.58	13.69	1.48
ETS	19.33	13.57	1.59
ETS-ARIMA	18.17	13.11	1.44

Forecasting without forecasters ARIMA modelling 27



# Which is the best forecast?



Go to [www.menti.com](https://www.menti.com) and use the code **90 68 80**

 Mentimeter

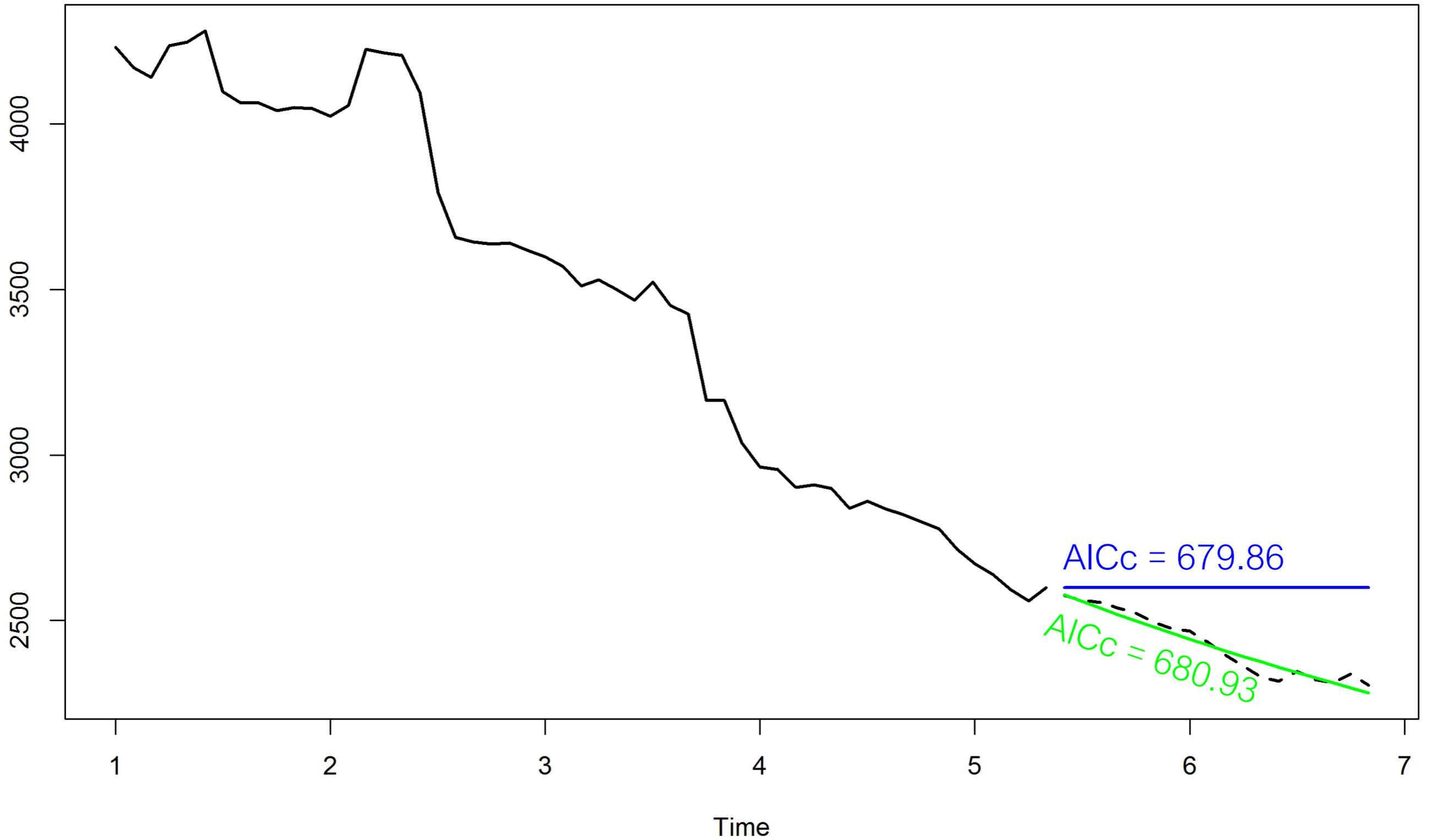
# Which is the best forecast?

0%  
Blue

0%  
Green

 0

# Which is the best forecast?



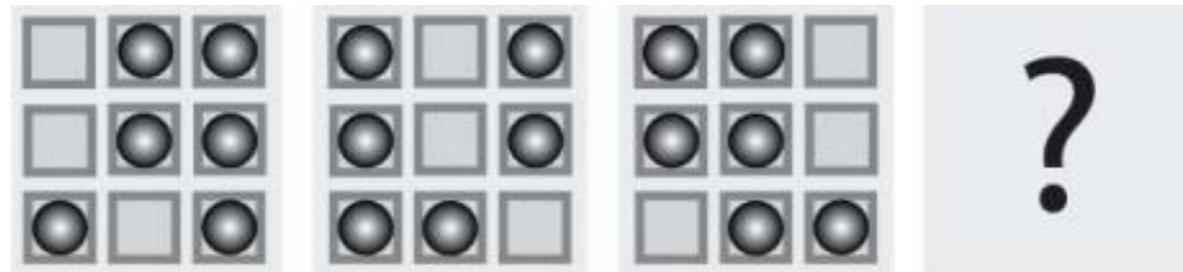
# Judgment & forecasting

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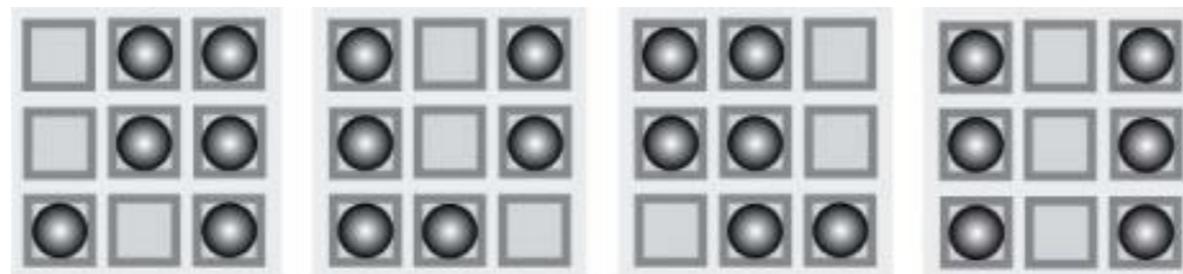
- Judgmental (point) forecasting  
Lawrence et al., 1985; 1986; Lawrence & Makridakis, 1989; Sanders, 1992; Makridakis et al., 1993; Goodwin & Wright, 1993; 1994; ...
- Judgmental adjustments of a statistical baseline  
Willemain, 1989; 1991; Mathews & Diamantopoulos, 1990; Goodwin & Fildes, 1999; Goodwin, 2000; Fildes et al., 2009; Syntetos et al., 2009; Franses & Legerstee, 2009; ...
- Judgmental probability forecasts and prediction intervals  
Weinstein, 1982; Wright & Ayton, 1989; 1992; Onkal & Muradoglu, 1994; Eggleton, 1982; O'Connor & Lawrence, 1992; ...
- Improving judgmental forecasts: feedback, decomposition, combining, ...  
Remus et al., 1996; Sanders, 1997; Goodwin & Fildes, 1999; Edmunson, 1990; Armstrong & Collopy, 1993; Lawrence et al., 1986; Blattberg & Hoch 1990; ...
- Judgmental model selection  
Bunn & Wright, 1991

# Forecasting with judgment: an IQ test analogy

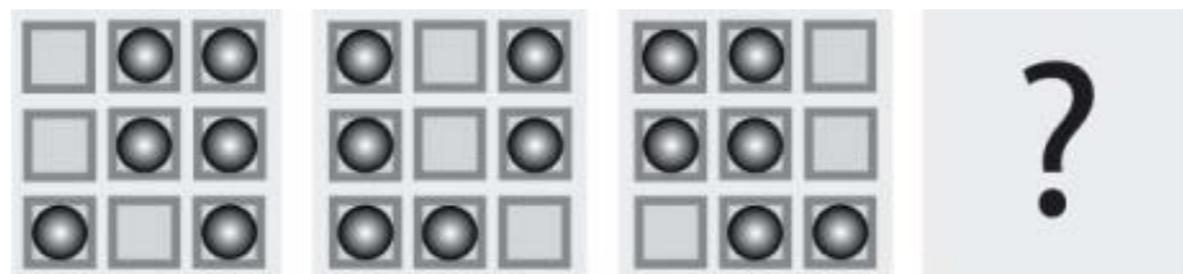
- Judgmental (point) forecasting



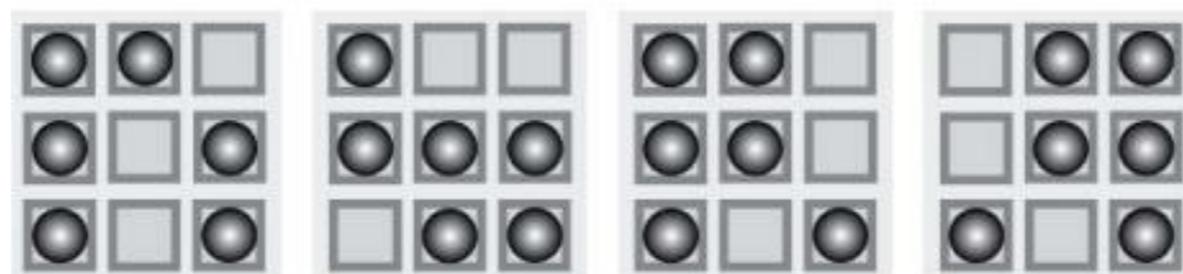
- Judgmental adjustments of a statistical baseline



- Judgmental model selection



← current study



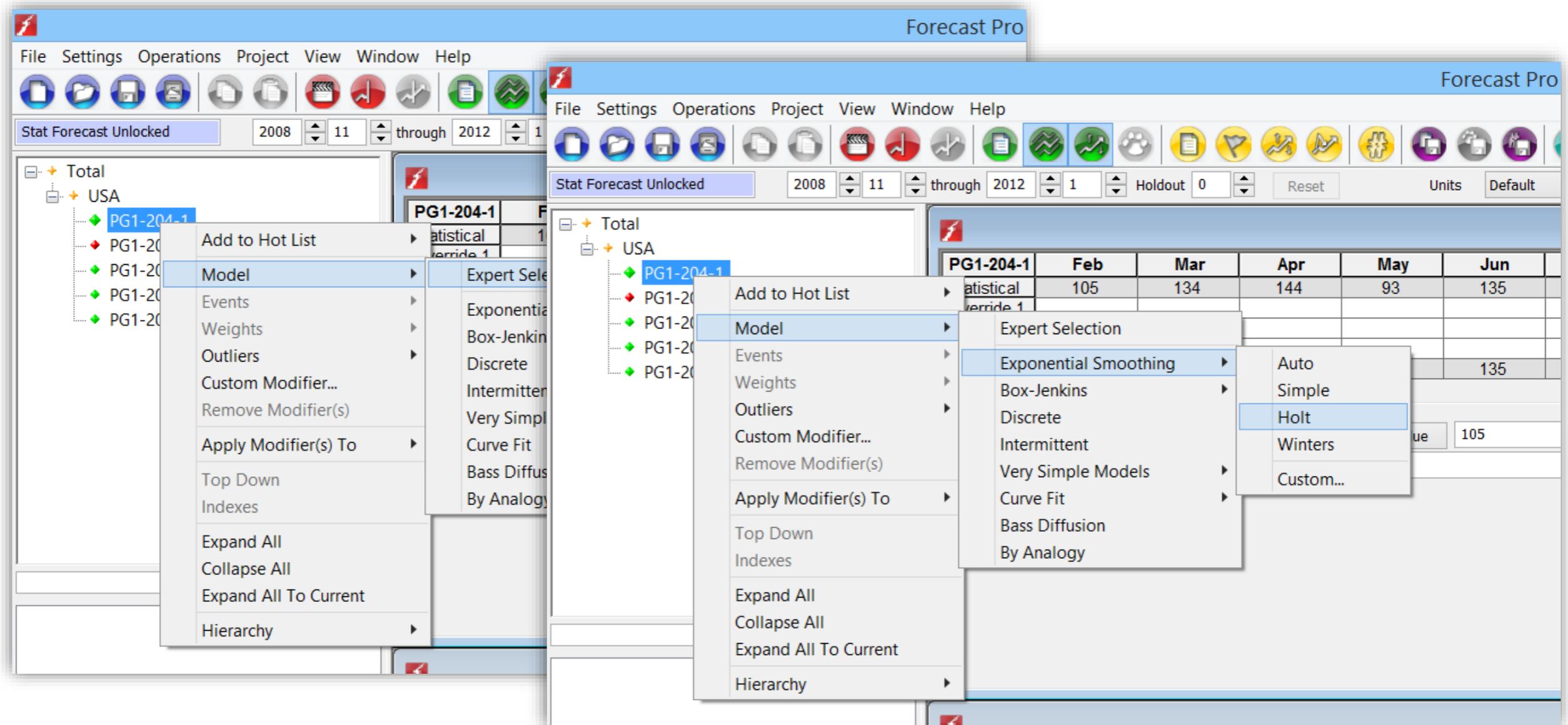
A

B

C

D

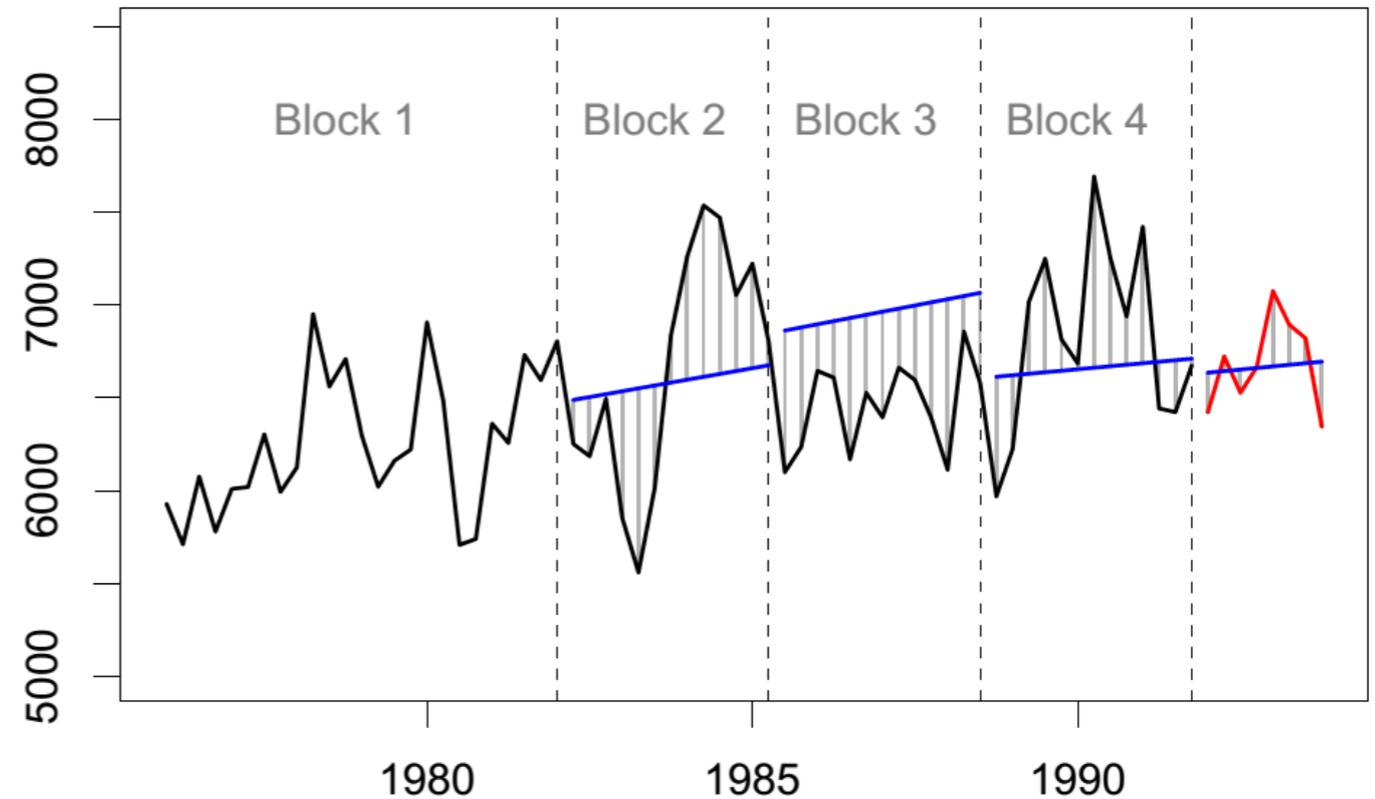
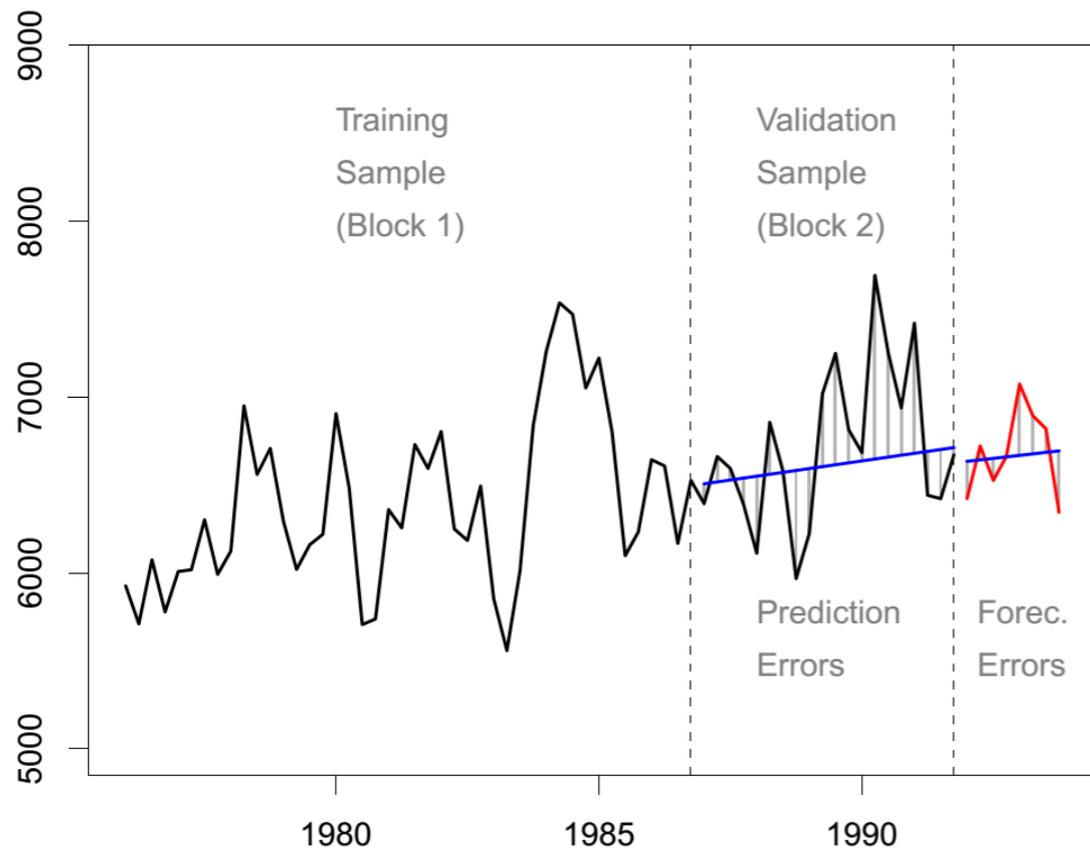
# Model selection in a FSS



- What about judgment?
  - This strategy is implied by the majority of the world-leading FSSs.
  - However, an empirical investigation of how subjects perform in such tasks is a research gap.

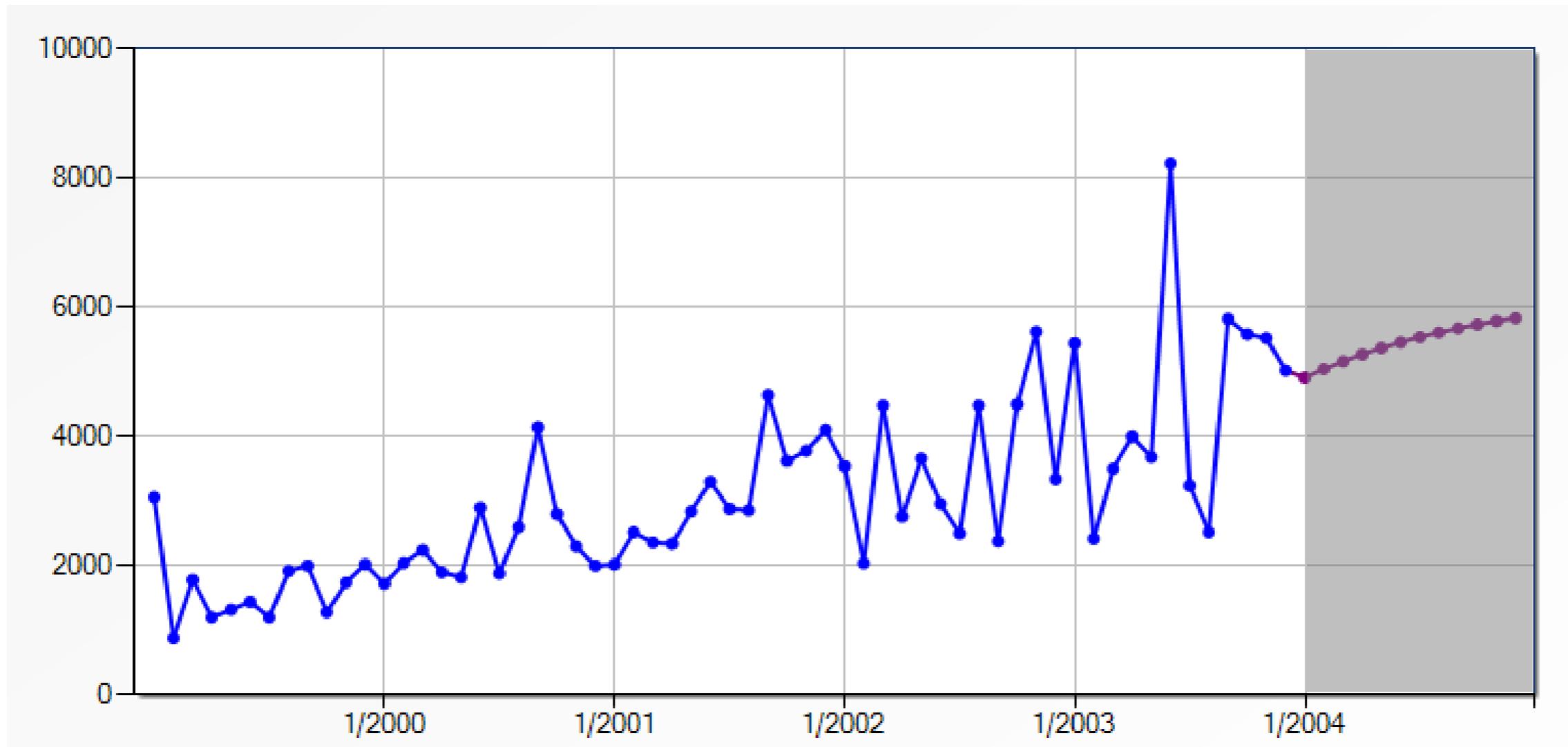
# Approaches for model selection

- Selection based on information criteria: AIC, BIC, AICc, ...
- Performance on a validation/cross-validation sample



- Rule-based selection

# Why do we expect to work?



- Statistical approaches cannot ex-ante assess the out-of-sample forecasts.
- Forecasters can select a method based on the quality of the out-of-sample forecasts.

# Hypotheses

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The **Brain**: Human Judgment = Judgmental Selection

The **Computer**: Forecasting System = Automatic Selection based on Information Criteria

**H1**: Brain performs model selection differently than Computer.

**H2**: Brain is better in building models than selecting ones.

**H3**: Combination and aggregation will outperform both Brain and Computer.

# Laboratory experiment

## Model Selection

## Model Build

The interface is divided into two main sections: Model Selection and Model Build.

**Model Selection:** A time series plot shows data points with a blue line. Below the plot, four radio buttons are labeled Model A, Model B, Model C, and Model D. A button labeled "Press only once!" is positioned below the radio buttons.

Model	Trend	Seasonality
Simple exponential smoothing (SES)	✗	✗
SES with seasonality	✗	✓
Damped trend	✓	✗
Damped trend with seasonality	✓	✓

**Model Build:** A time series plot shows data points with a blue line. Below the plot, a "Seasonal Plot" shows data points with a blue line. A button labeled "Submit" is positioned below the seasonal plot. A note below the button reads: "If you are confident with your selection, you can proceed to the next series by clicking once on the 'Submit' button." Below the button, a button labeled "Press only once!" is positioned.

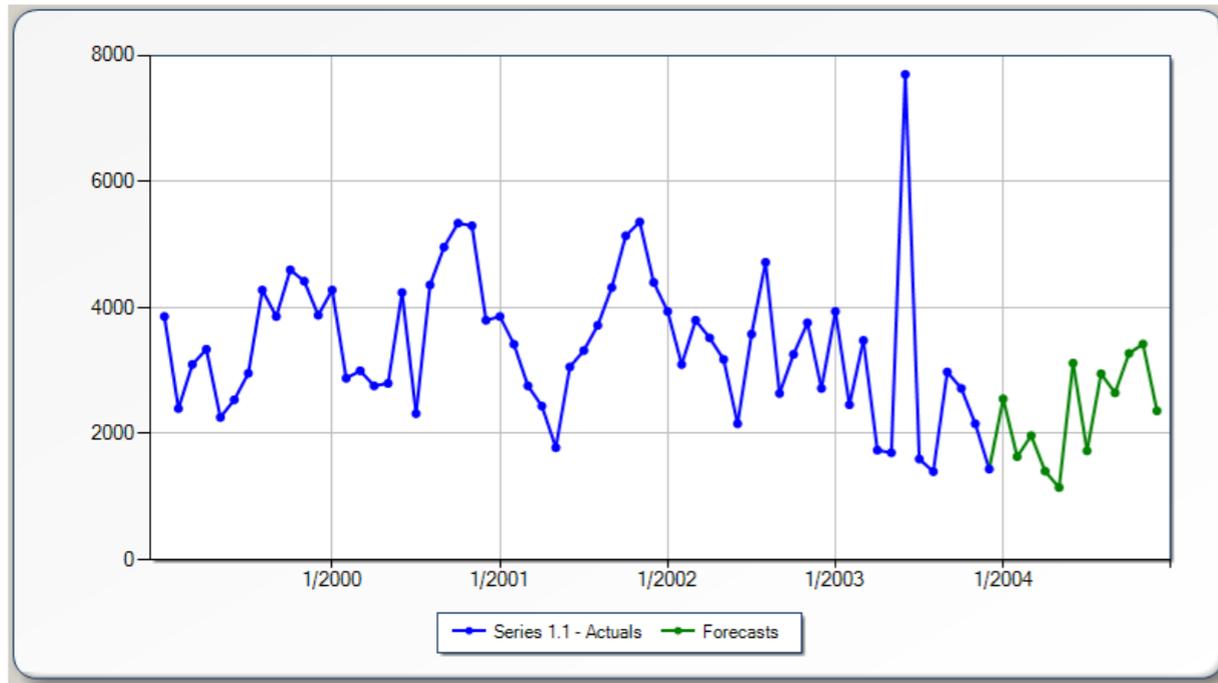
**Select patterns that are applicable (if any):**

- Trend
- Seasonality

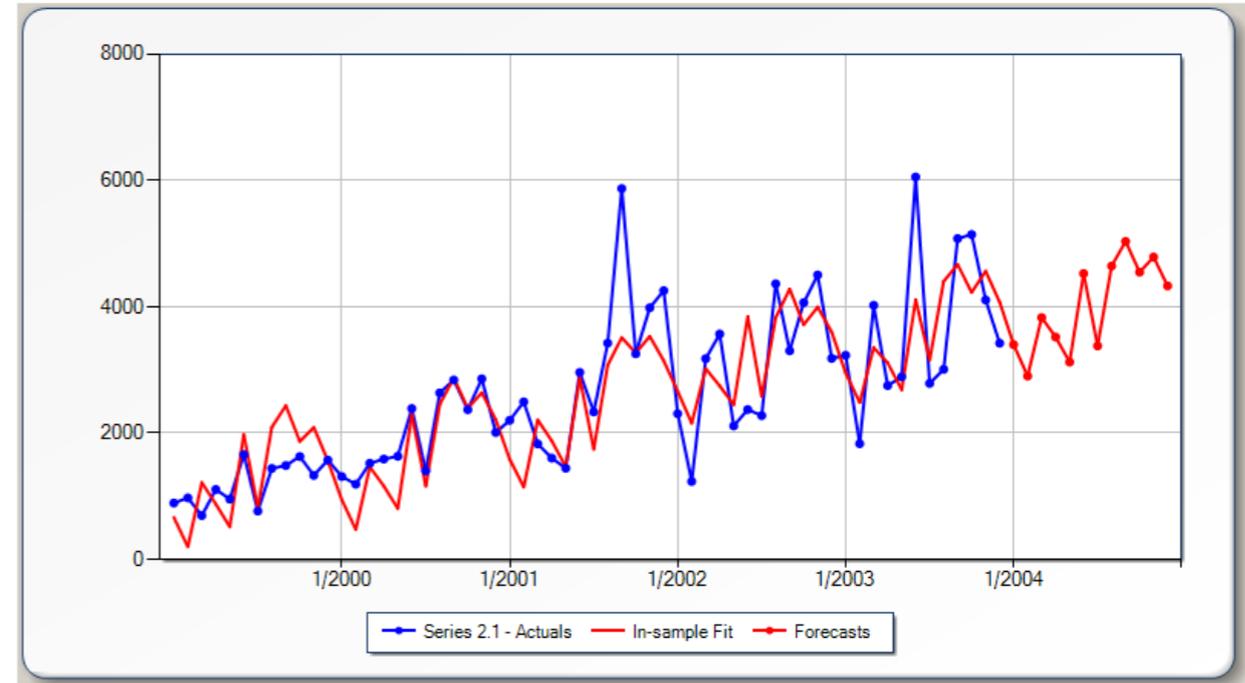
Each participant was randomly assigned in one of the two approaches and was asked to provide selections for 32 time series, based on different types of information.

# Types of information

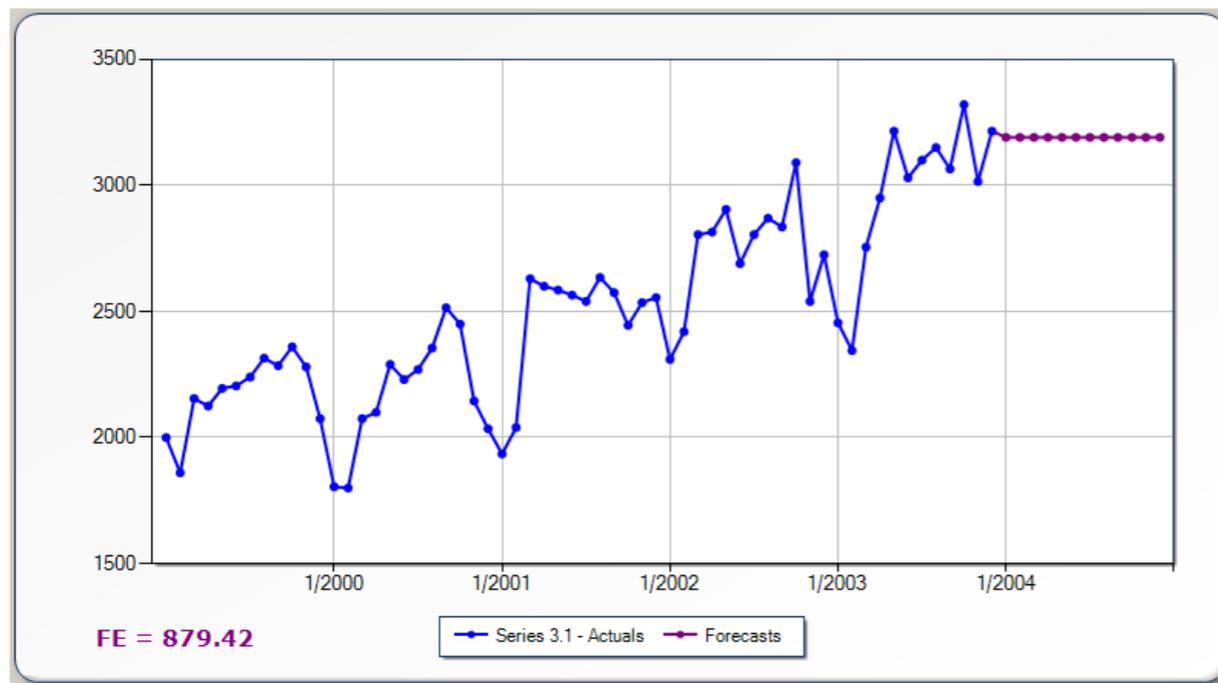
## Out-of-sample forecasts only



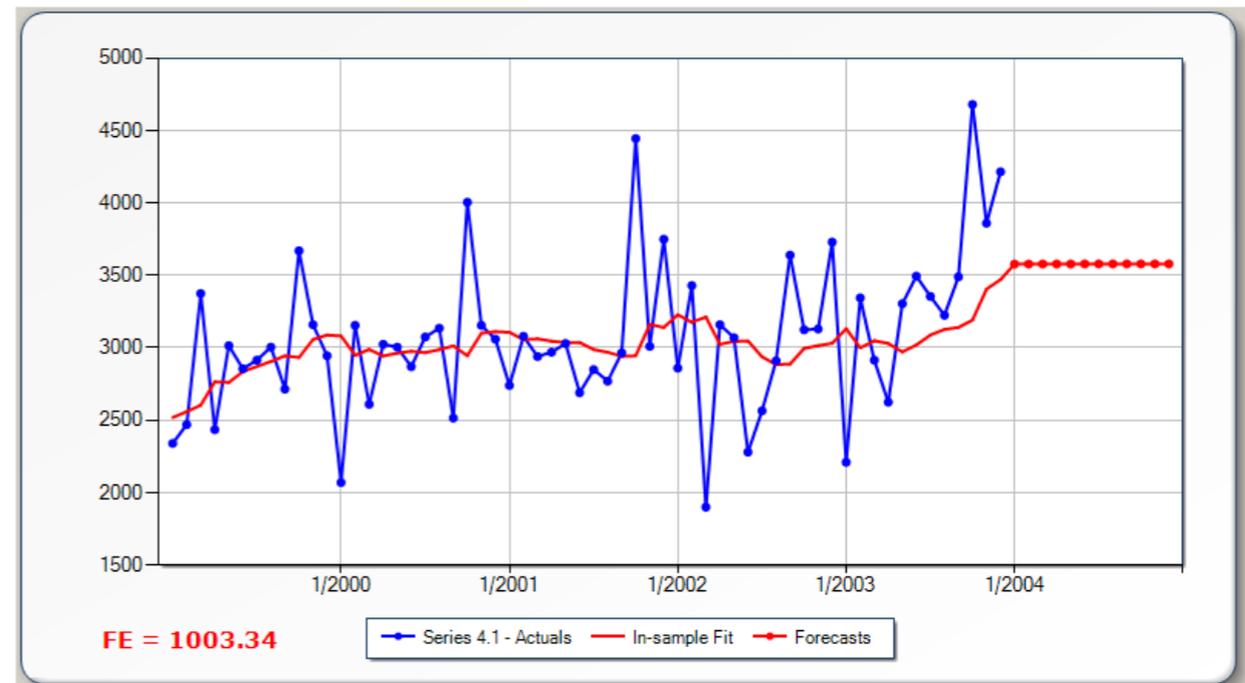
## In-sample fit and out-of-sample forecasts



## AIC value and out-of-sample forecasts



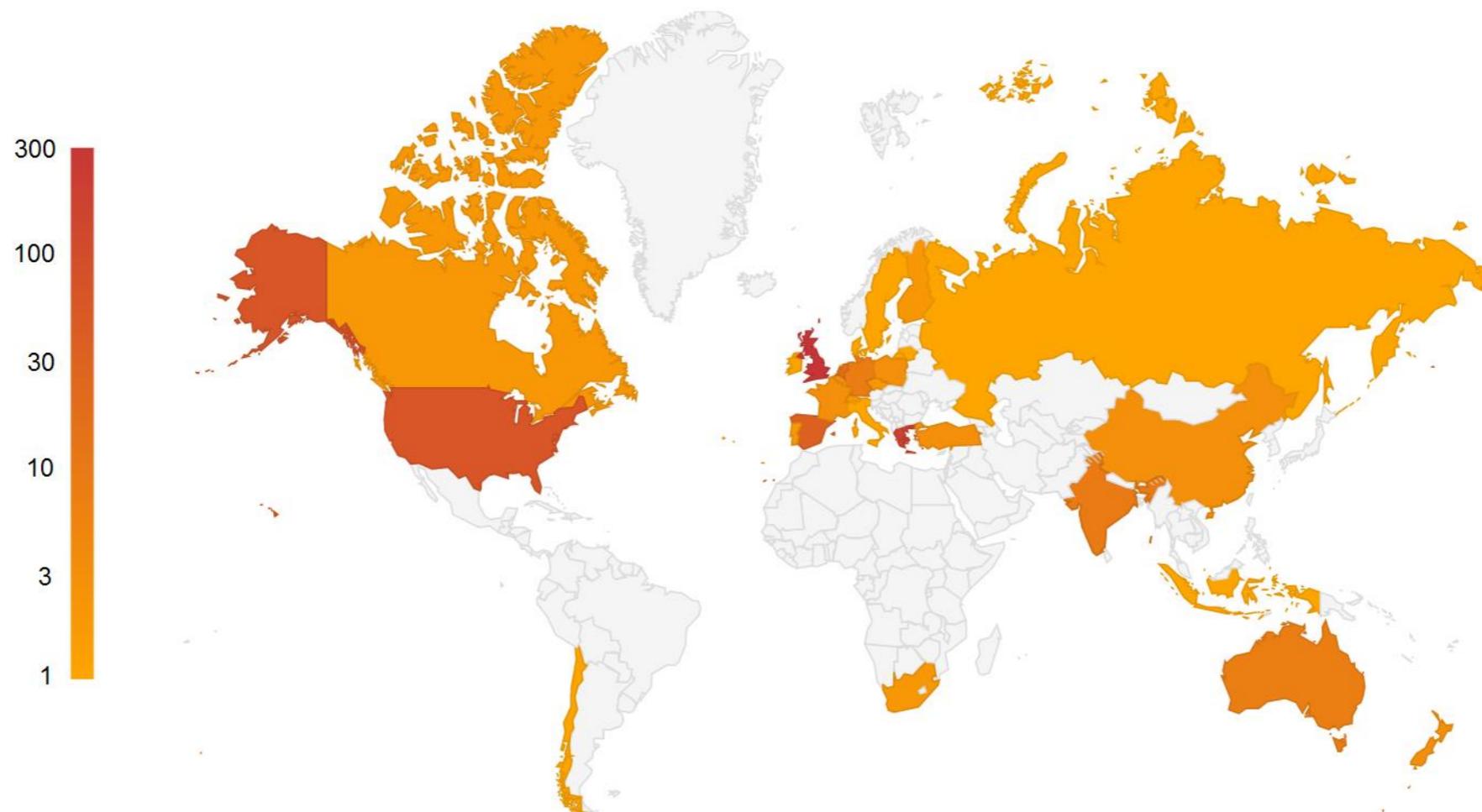
## In-sample fit, AIC value and out-of-sample forecasts



# Participants

Role	Model Selection	Model Build	Total
UG students	139	137	276
PG students	103	108	211
Researchers	13	31	44
Practitioners	46	44	90
Other	40	32	72

**693**  
participants



# Individual judgmental selections

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Model A      0

Model B      0

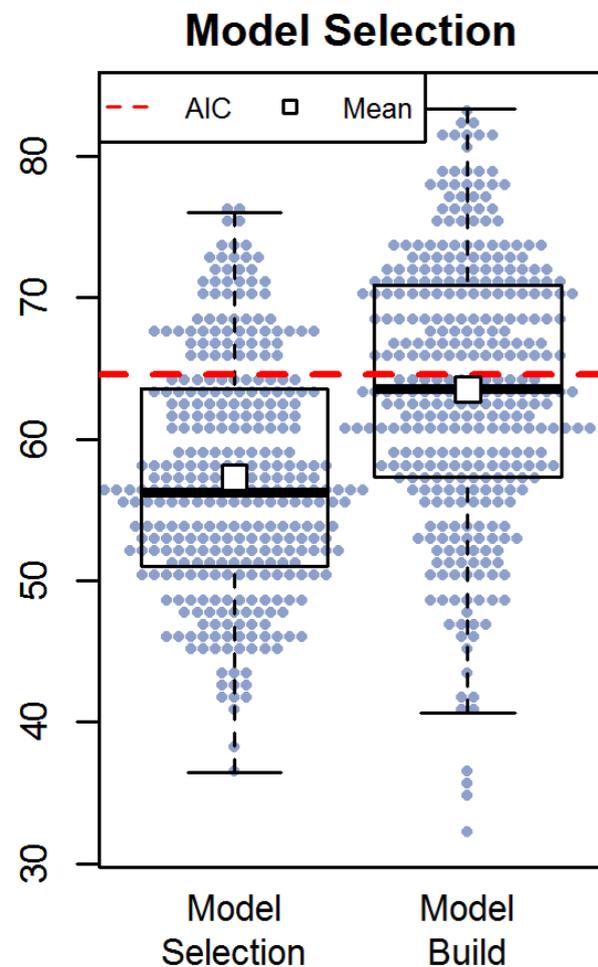


Model C      1

Model D      0

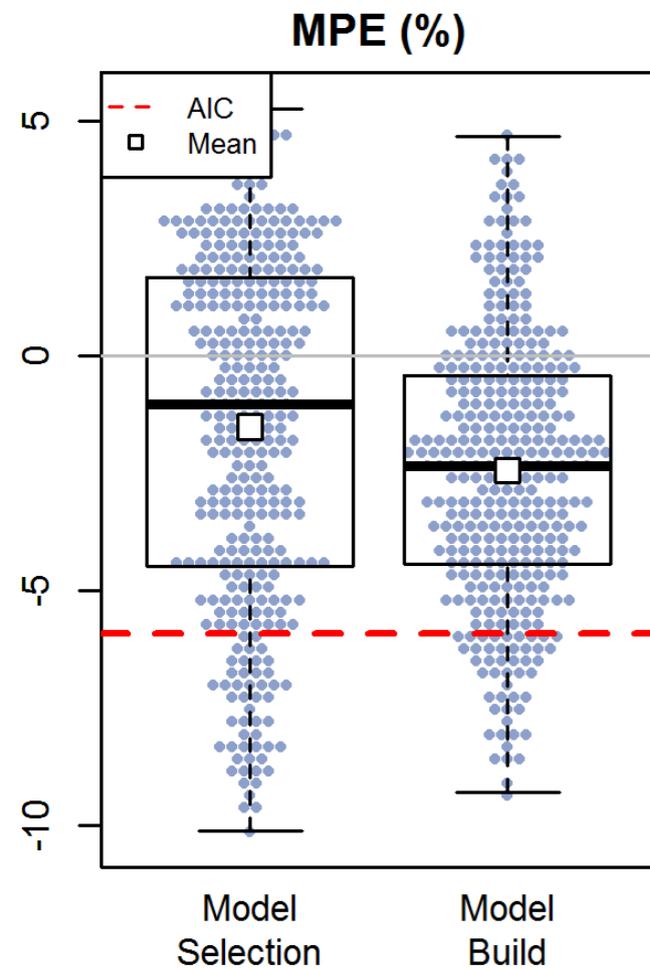
# Selecting models judgmentally

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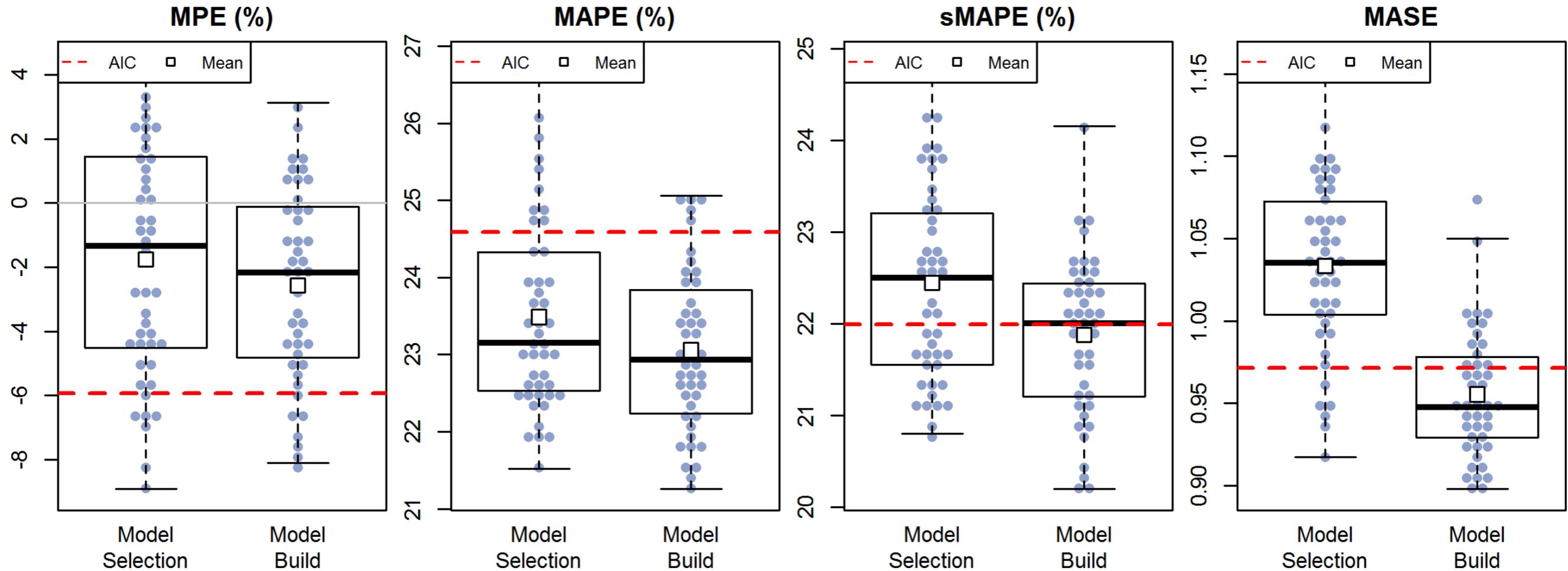
- Overall, humans' score is lower than statistics...  
...while they select the ex-post best model less frequently.
- However, they do succeed in avoiding the worst model.
- How does this translate to forecasting performance?

# Forecasting performance overall



- In terms of bias and MAPE, humans perform significantly better than AIC.
- Participants in the Model Build experiment are as good as statistics, in terms of sMAPE or MASE.

# Forecasting performance of practitioners



- Practitioners on “model build” approach generally outperform the statistical model selection.

# 50% statistics + 50% manager [Blattberg & Hoch, 1990]

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Model A

$$\frac{1}{2} = 0.5$$

Model B

$$\frac{0}{2} = 0$$



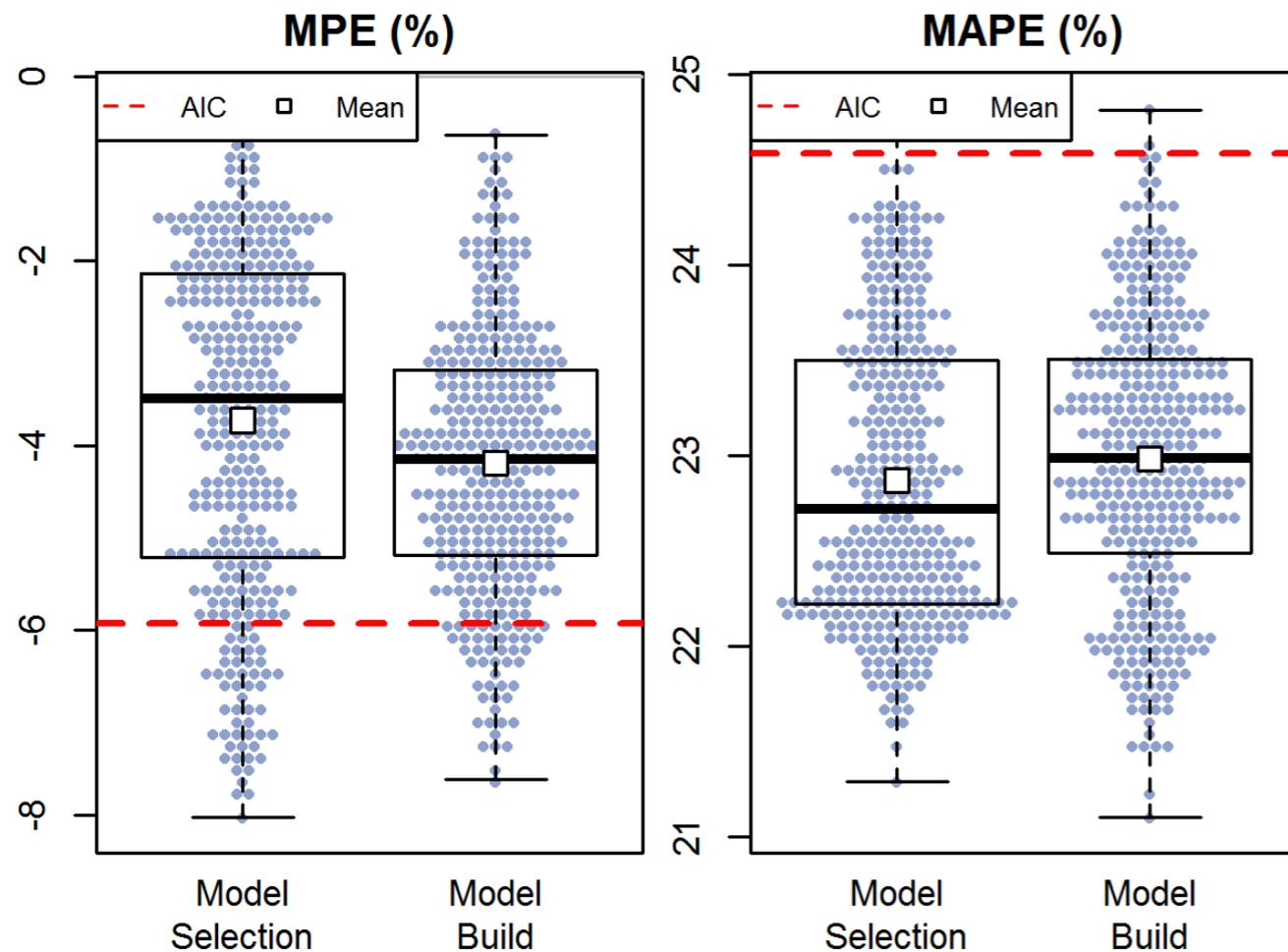
Model C

$$\frac{1}{2} = 0.5$$

Model D

$$\frac{0}{2} = 0$$

# 50% statistics + 50% manager: results



- The Blattberg-Hoch approach works for 86% of the cases for bias, 99% of the cases for MAPE and sMAPE and for 90% of the cases for MASE.
- The differences in the performance between the two approaches (model selection and model build) are also minimised.

# Wisdom of crowds

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Model A

$$\frac{6}{20} = 0.3$$



Model B

$$\frac{8}{20} = 0.4$$



Model C

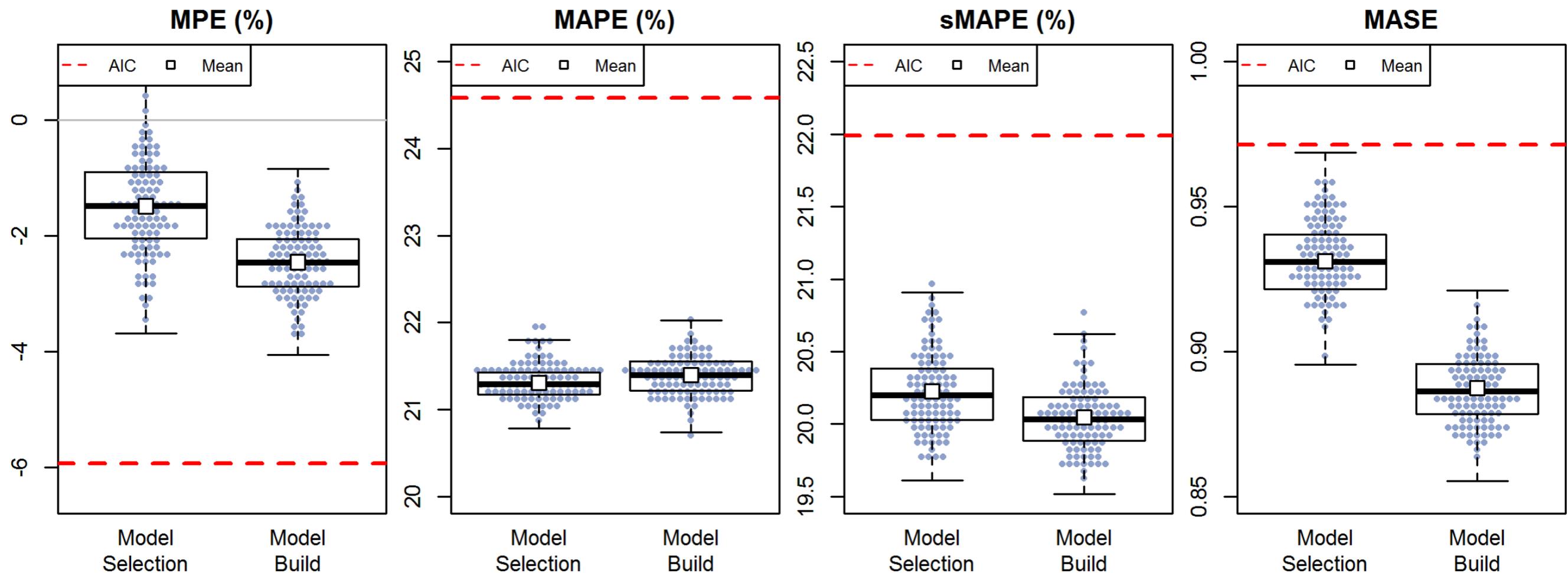
$$\frac{2}{20} = 0.1$$



Model D

$$\frac{4}{20} = 0.2$$

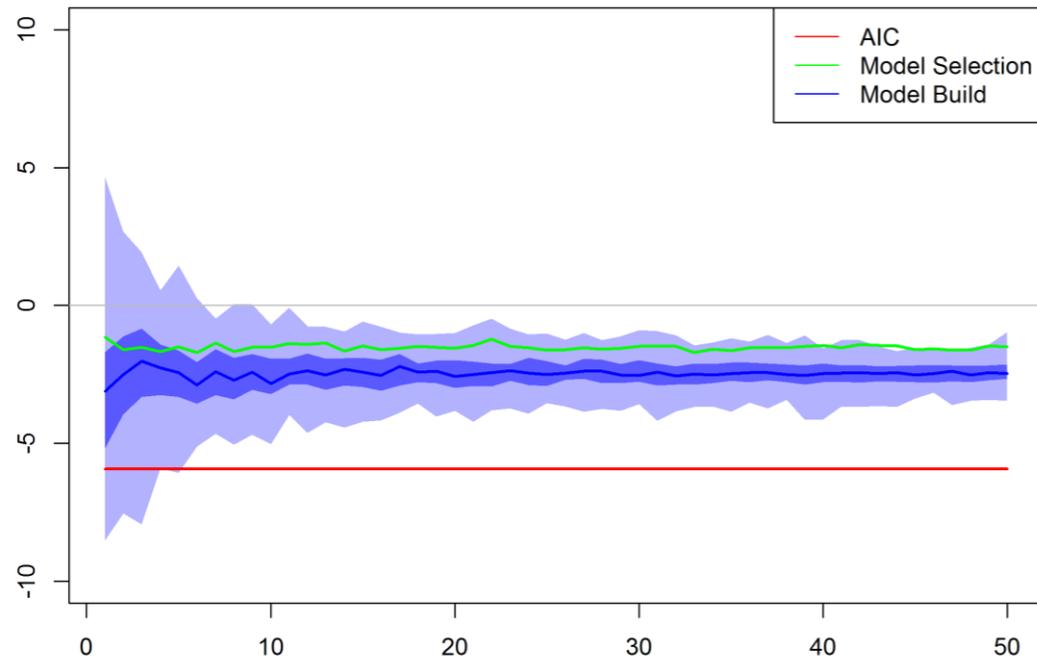
# Wisdom of crowds: results



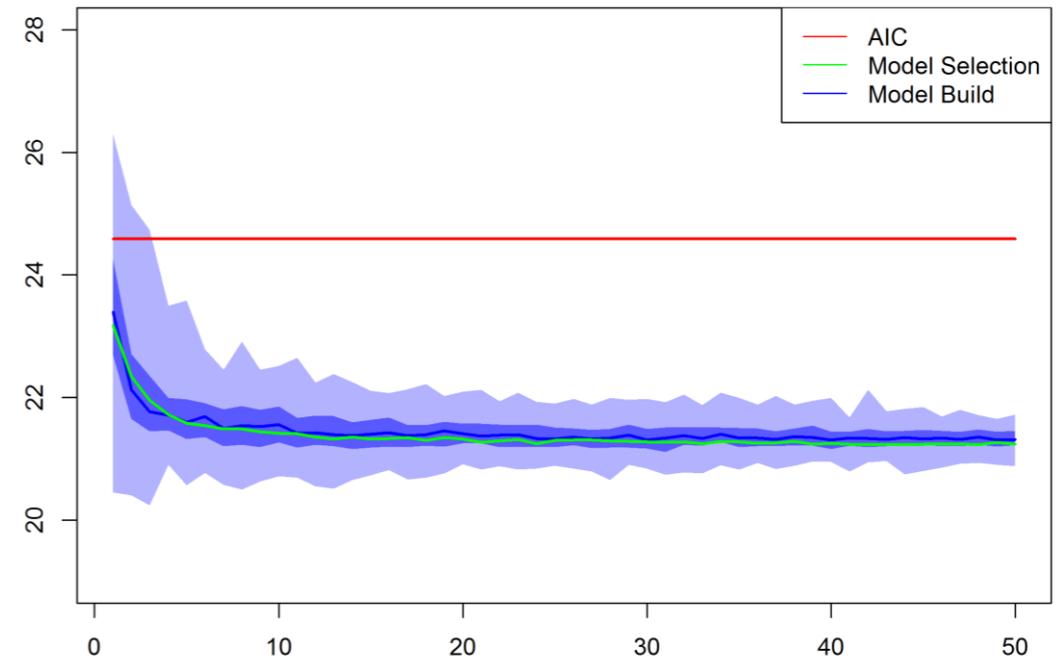
- 20 experts: the forecasting performance of a grouped judgmental model selection approach is significantly better than statistical model selection.
- How many experts are enough?

# Wisdom of crowds: results (cont'd)

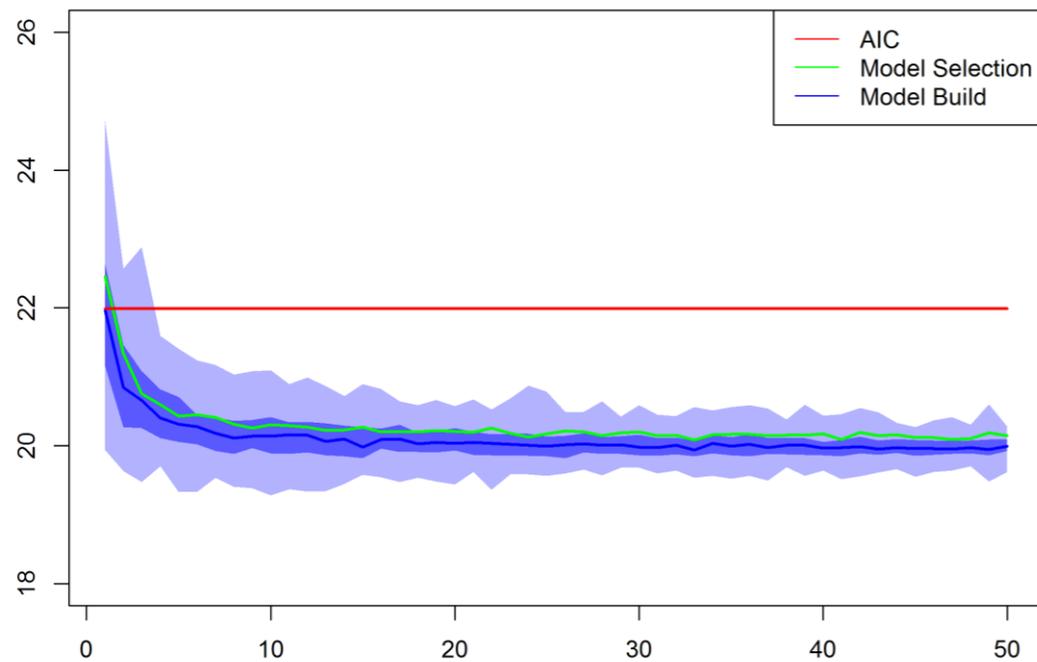
MPE (%)



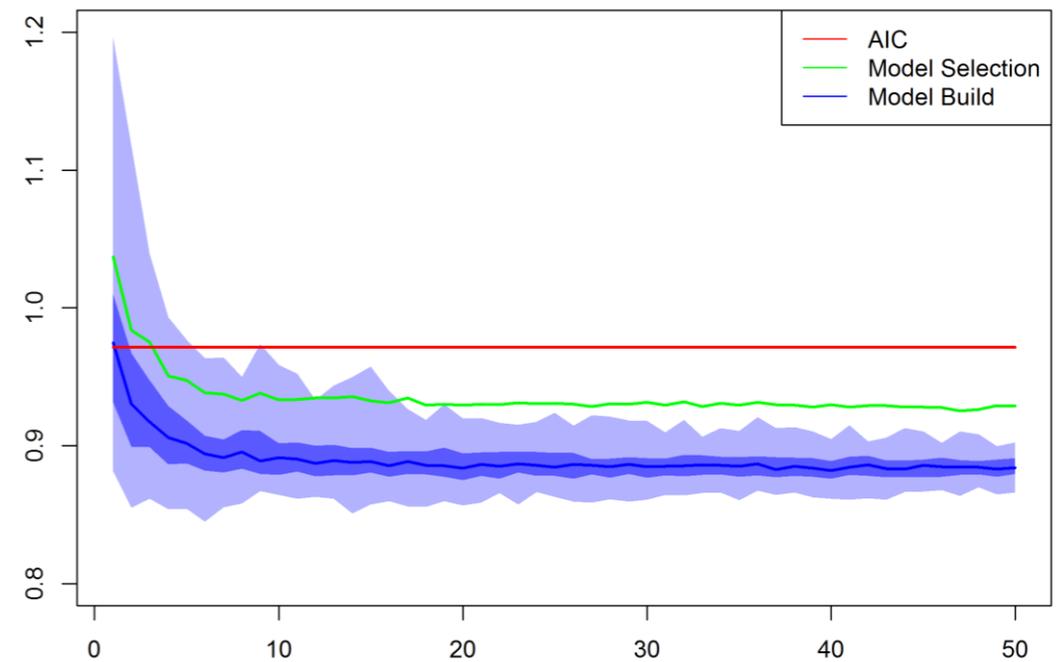
MAPE (%)



sMAPE (%)



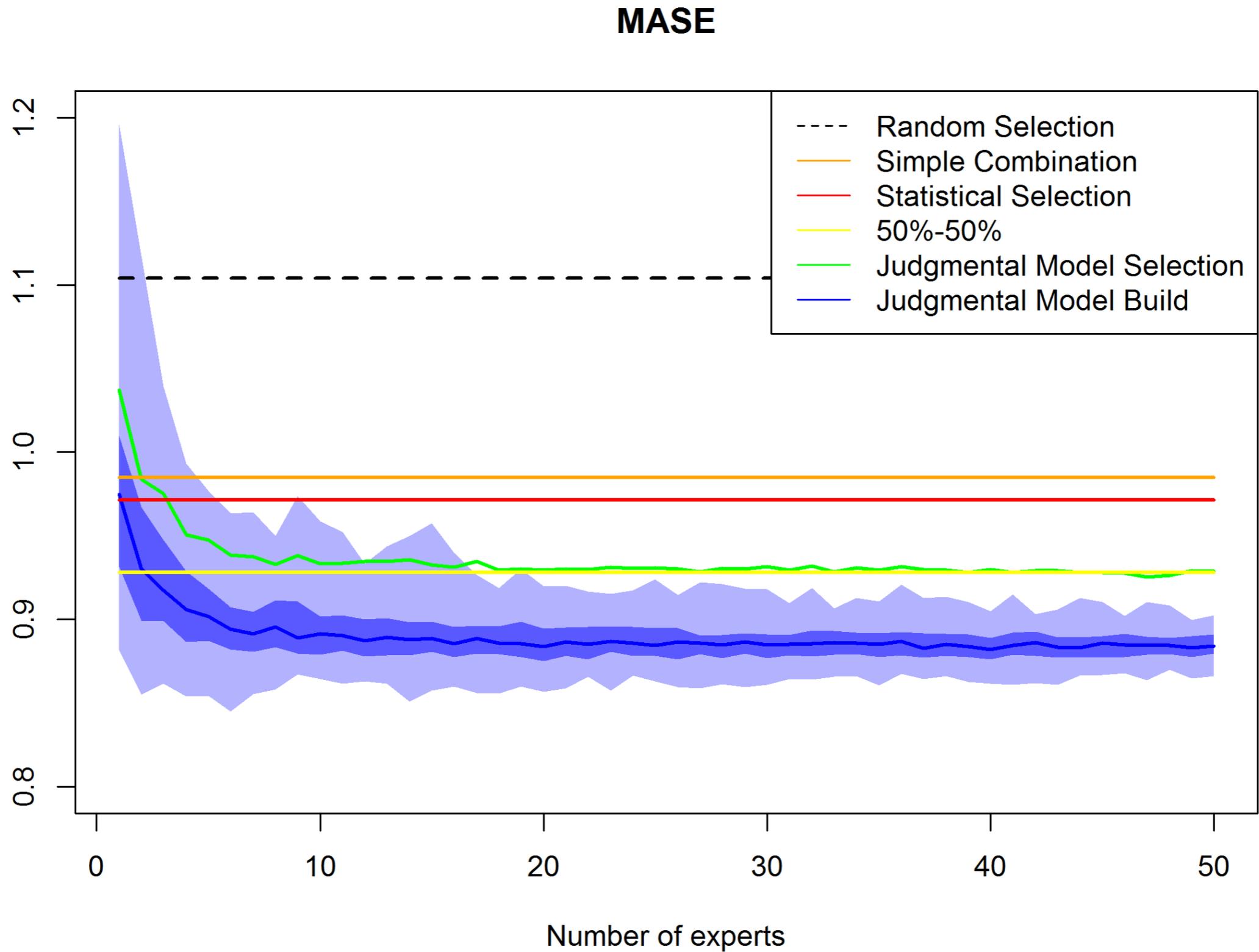
MASE



Number of experts

Number of experts

# Summary of results



# ABCXYZ analysis

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Forecastability	High	AX	BX	CX
		AY	BY	CY
	Low	AZ	BZ	CZ
		High		Low
		Importance		

→ Focus on the important (A) and least forecastable (Z) items.

# Conclusions

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- Judgmental model selection is offered by every FSS, but its performance has never been empirically evaluated before.
- Judgmental model selection and, especially, model build may offer improvements over a statistical selection strategy.
- The improvements are more apparent when we focus on the participants self-described as practitioners.
- Wisdom of crowds (grouped judgmental model selection) or a 50%-50% combination approach appear to be very promising.

# Next step: brain imaging

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- Simplified experiment to identify the decision making process for model selection versus model build.
- Electroencephalogram (EEG) is used to capture the brain activity during the two tasks.

# Thank you!

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