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Bayesian Trend Selection

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Ratemaking and Product Management (RPM) Seminar
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Overview

- Objective
- Trend Analysis—Status Quo
- Bayesian Trend Selection
- Case Study
- Model Validation
- Conclusion

2013, *eForum, forthcoming,* www.casact.org/pubs/forum/
The paper is available at www.ncci.com/nccimain/IndustryInformation/ResearchOutlook/Pages/BayesianTrendSelection-Research.aspx

Objective

- Provide a tool for decision making under uncertainty within the existing NCCI framework of trend analysis and selection
- The development of a new forecasting model is out of scope
  - The time series used in trend selection are extremely short

Trend Analysis
Current Framework

- Selecting loss ratio trends is an integral part of NCCI aggregate ratemaking
  - Accounts for (some of) the difference between the experience period and the effective period
- The selection process considers
  - Results from various models
  - Exogenous information

Trend Analysis
Models Considered

- Model results typically considered during the selection process generally originate from three exponential trend (ET) models
  - 5-point ET, which is a regression of the past 5 natural logarithms on a linear time trend
  - 8-point ET
  - 15-point ET
- The nature of the data generating process determines the theoretically optimal model among the three

Trend Analysis
Considering the Data Generating Process

- The statistical quality of an estimate can be quantified in terms of its
  - Bias: How *relevant* is the answer?
  - Variance: How *reliable* is the answer?
- If the data generating process is unchanged,
  - All observations are relevant
  - Incorporating more observations in the regression will reduce the variance of the estimate
- If the data generating process has recently changed,
  - Older observations fundamentally differ from newer observations
  - Incorporating these fundamentally different observations in the regression will increase the bias of the estimate

Trend Analysis
The Role of Actuarial Judgment

- Actuarial judgment serves as the final step in the trend selection process
- Actuarial judgment aggregates the results of the three previously mentioned ET models
  - Taking into account a variety of influences such as the presence (or absence) of recent reforms

Decision Making Under Uncertainty

- Academic research suggests that human decision making can be subject to systematic errors
  - Representativeness
  - Availability
  - Adjustment and Anchoring
- The Bayesian Trend Selection (BTS) provides an answer free from such potential biases
  - At the cost of ignoring information that does not manifest itself in the observed data

The Role of The Bayesian Trend Selection

- The BTS is intended to serve two distinct, yet related, roles:
  1. Objectively aggregate the results of the various fundamental models into a single forecast
     - In parallel with actuarial judgment
  2. Provide objective insight into relative appropriateness of each model
     - Input for the actuarial judgment process

The Bayesian Trend Selection
Specifics

- BTS directly estimates
  - Indemnity loss ratio trend
  - Medical loss ratio trend
  - Frequency trend
- Using the loss ratio and frequency estimates, BTS indirectly estimates
  - Indemnity severity trend
  - Medical severity trend

The Bayesian Trend Selection
Estimation: Loss Ratios and Frequency

- The BTS considers how well each of the three ET models performed in the recent past for each series (in isolation) using the three most recent NCCI ratemaking data sets
  - Each data set is split into a training and a holdout set
    - The holdout period consists of three years, which parallels the typical trend period
  - Each of the three ETs are estimated on each of the training sets
    - Nine estimates in total
  - The three estimates from each ET are compared to the three compound annual growth rates observed in the respective holdout periods

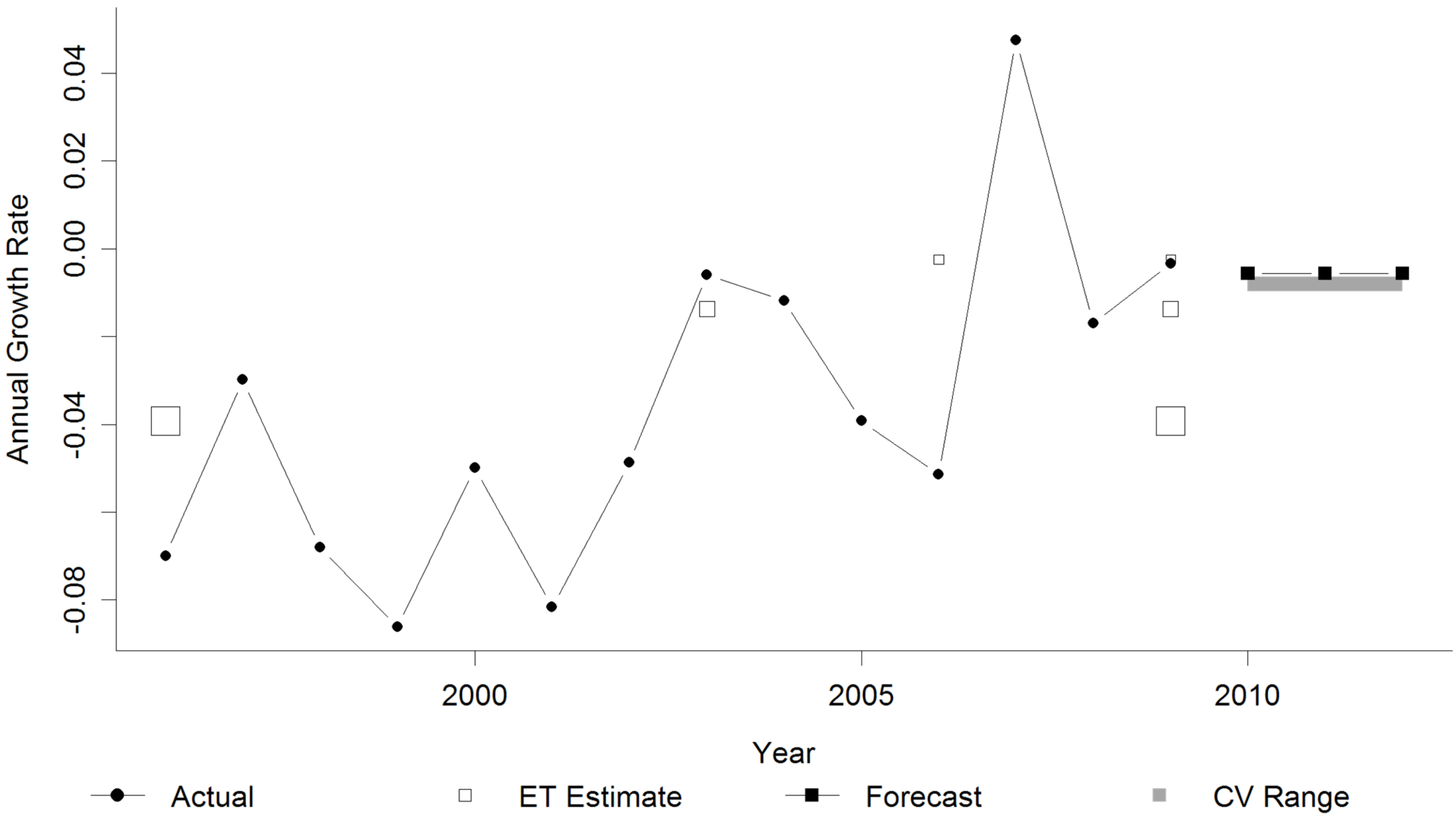
The Bayesian Trend Selection
Estimation: Loss Ratios and Frequency

- The BTS produces two estimates
  - The posterior probability that the compound annual growth rates observed in the holdout sets were "truly" generated from a given ET forecasts
    - A Model Selection paradigm
  - The BTS growth rate estimate, which weights the three ET forecasts (using the most recent full data set) together using these posterior probabilities
    - A Model Averaging paradigm

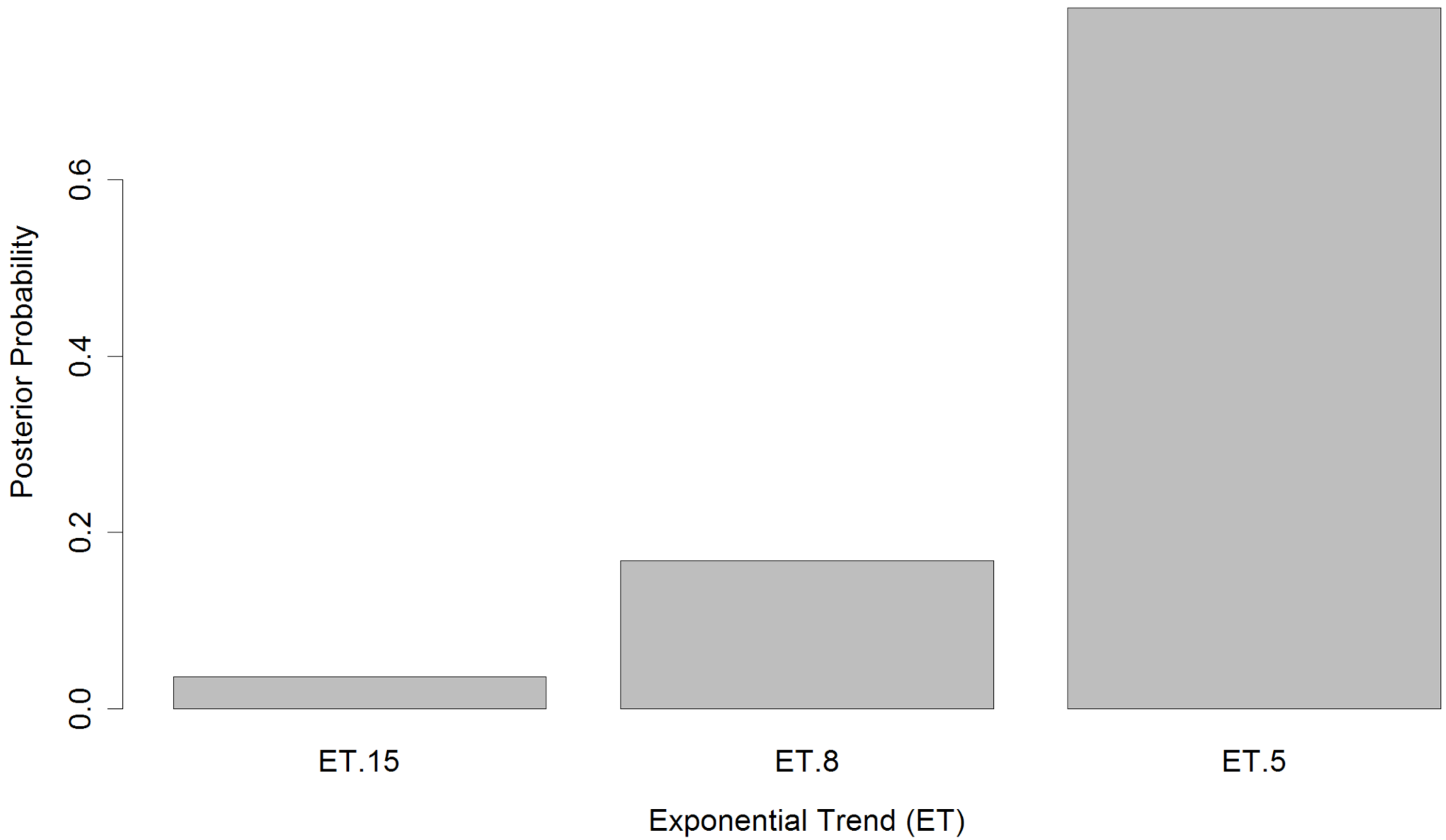
Case Study

- Applying the BTS to an unidentified state illustrates the concept
- The indemnity loss ratio growth rates exhibit systematic differences between newer and older time periods
  - As such, the BTS gives more weight to ETs that use only more recent observations
- The medical loss ratio growth rates exhibit fewer systematic differences between newer and older time periods
  - As such, the BTS gives more weight to ETs that use more observations

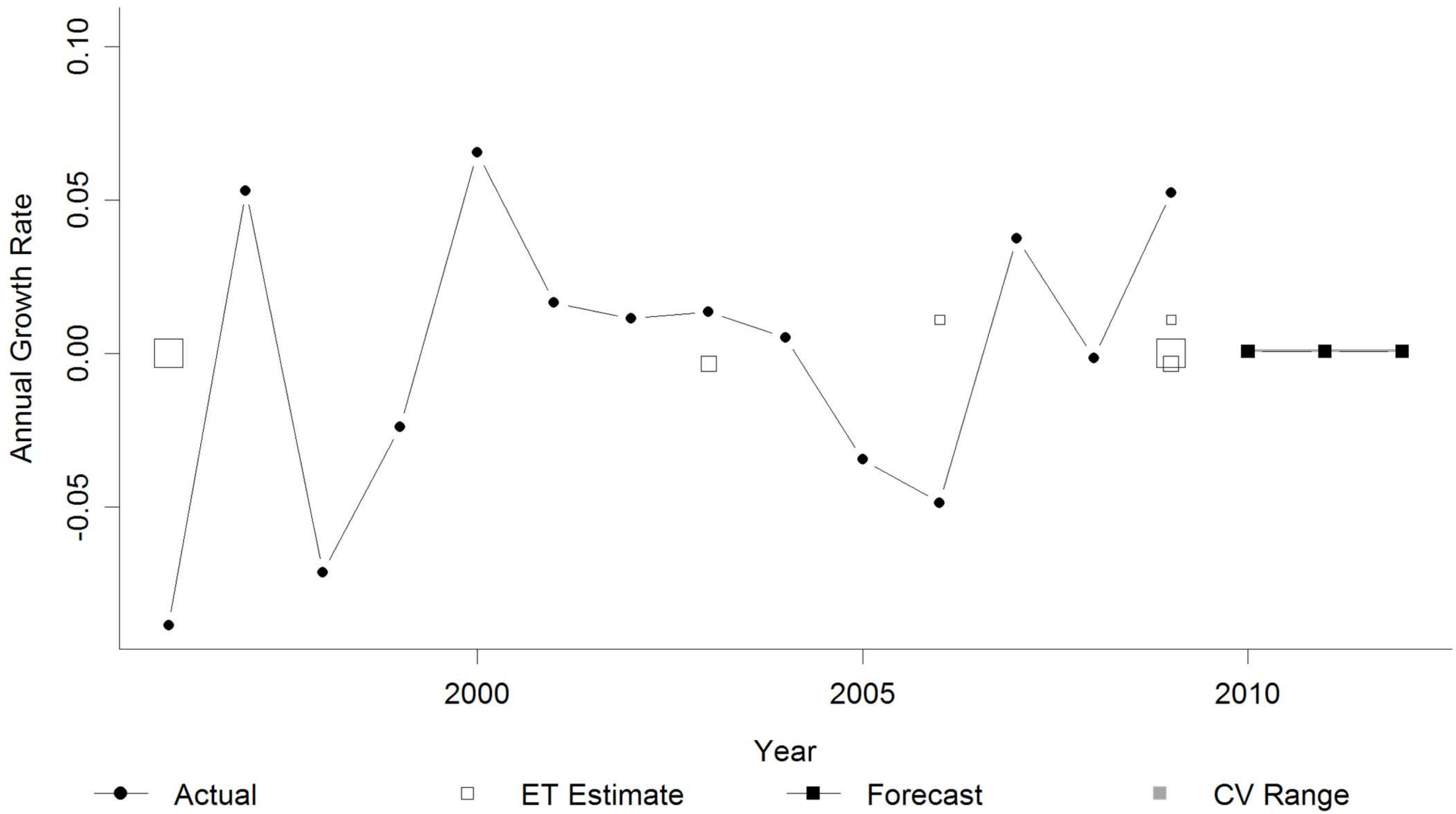
Indemnity Loss Ratio
Select State: Growth Rates



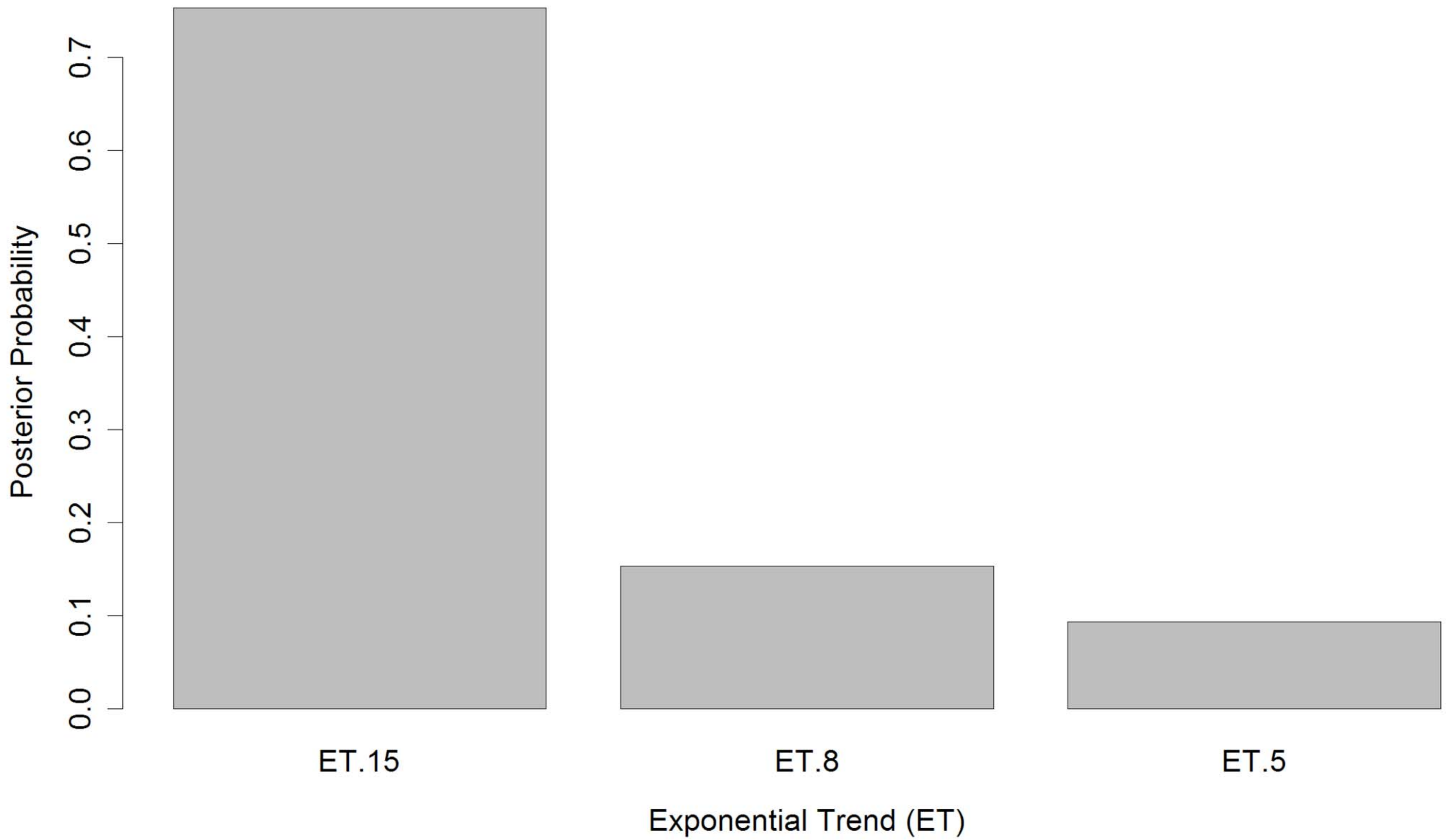
Indemnity Loss Ratio
Select State: Posterior ET Probabilities



Medical Loss Ratio
Select State: Growth Rates



Medical Loss Ratio
Select State: Posterior ET Probabilities



Model Validation

- The BTS is validated using two data sets
- The first data set
  - Consists of NCCI ratemaking data for 29 states
  - Allows for only one hold out period but consists of many series
- The second data set
  - Consists of incidence rates of workplace injuries (and illnesses) for the manufacturing industry
  - Allows for many (consecutive) hold out periods but consists of only one series

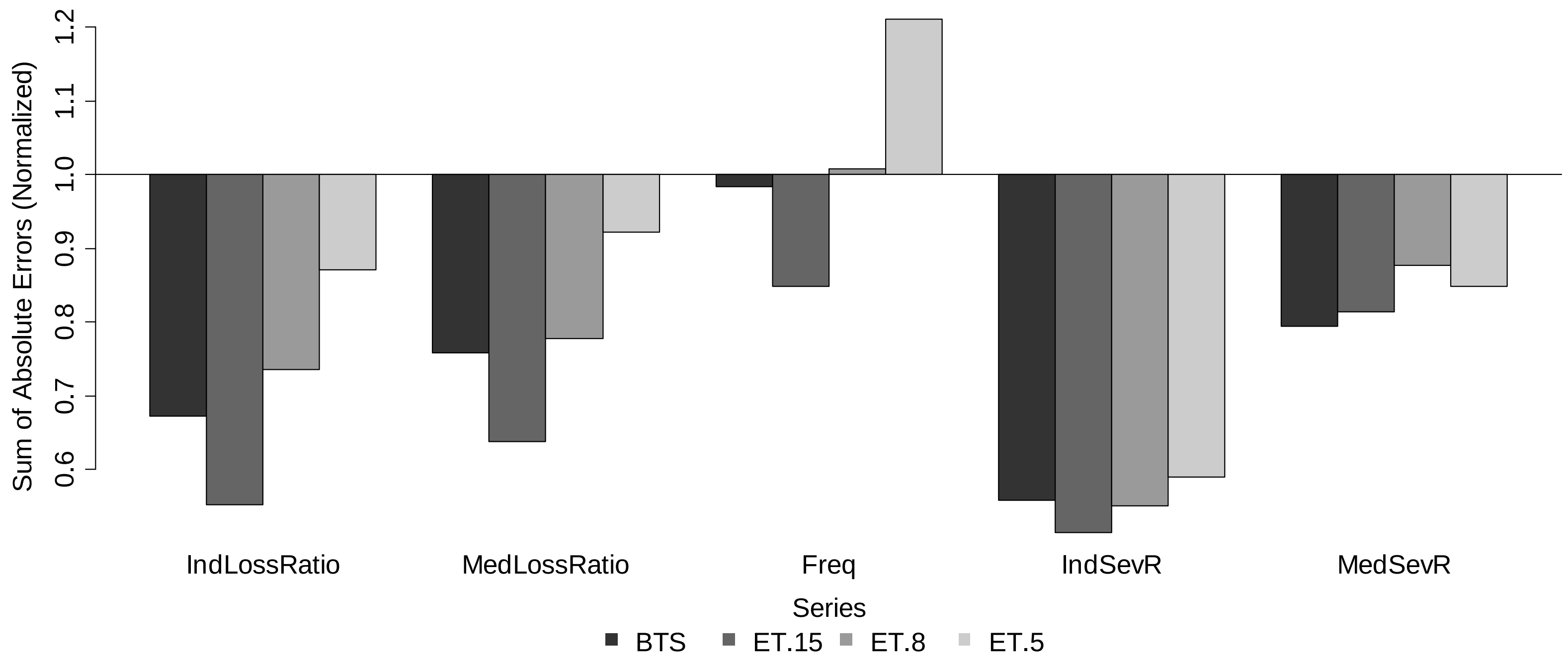
Model Validation

Goals

- The BTS formalizes the actuarial judgment step in trend selection
  - The BTS proves a valid model if it can objectively “select” among the three competing ETs
    - It is sufficient to show that the BTS estimate is better than the worst possible choice among the three ETs
      - Where the worst possible choice depends on the nature of the series
- This validation process seeks to show that choosing the BTS estimate is a robust decision

Sum of Absolute Forecast Errors

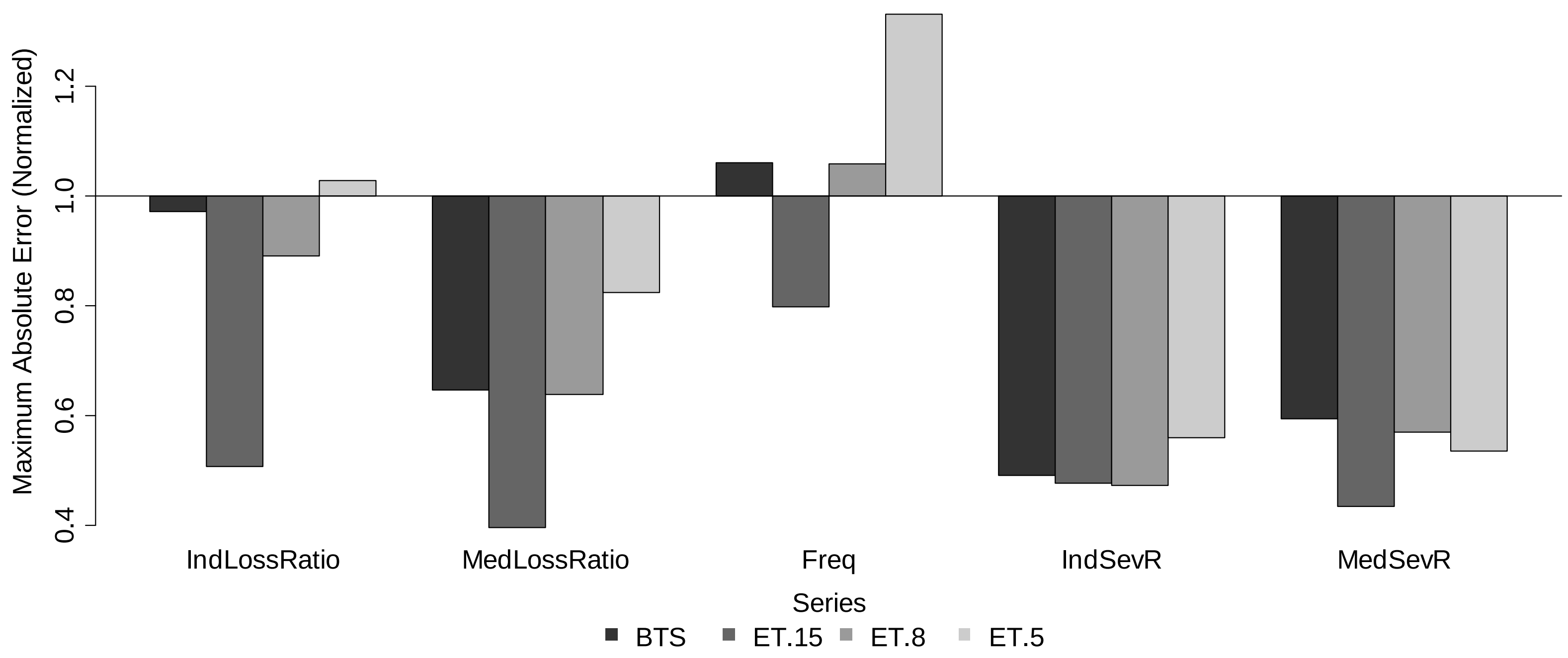
NCCI Ratemaking Data



The values shown are normalized (i.e., divided) by the corresponding value associated with the random walk estimate

Maximum Absolute Forecast Error

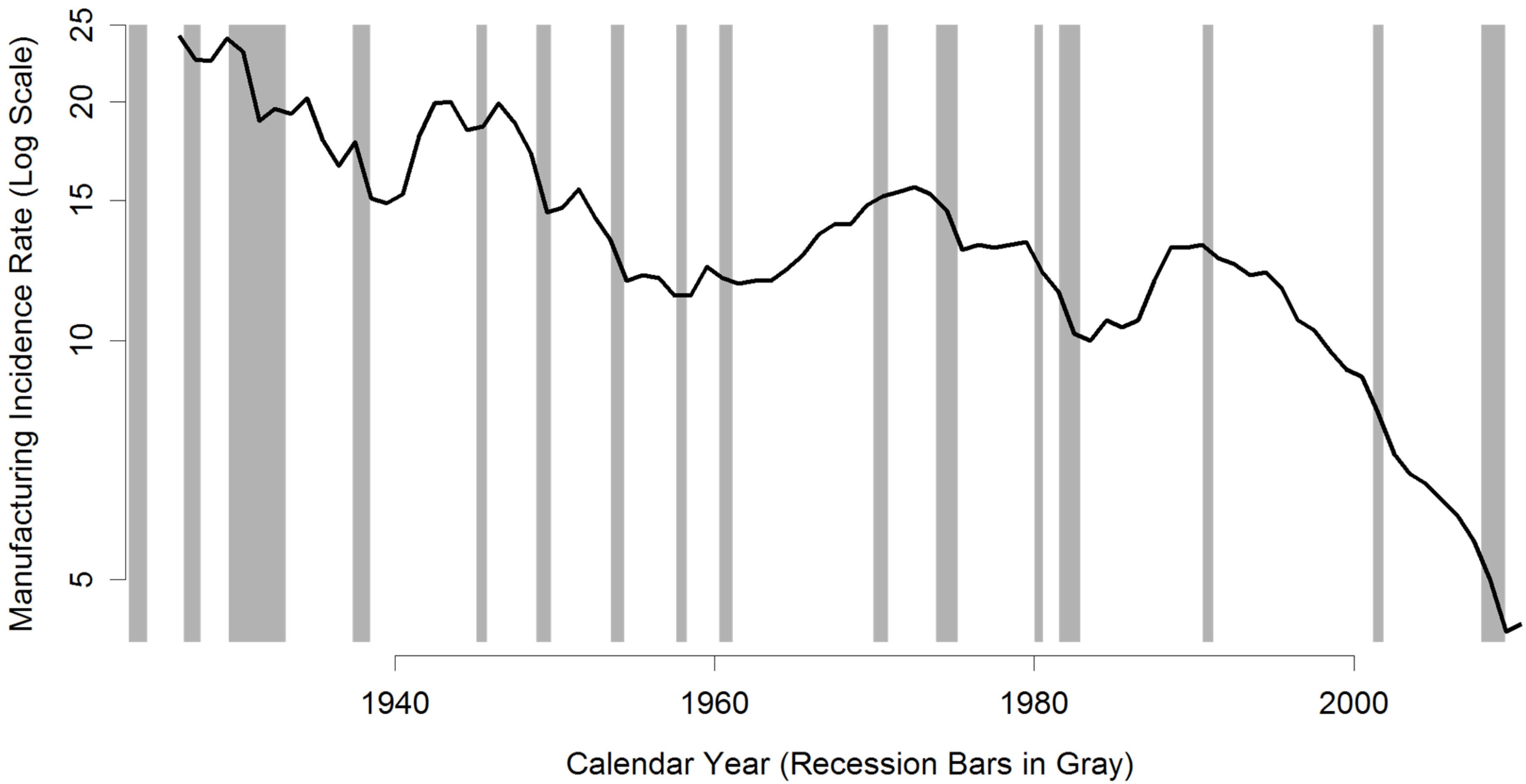
NCCI Ratemaking Data



The values shown are normalized (i.e., divided) by the corresponding value associated with the random walk estimate

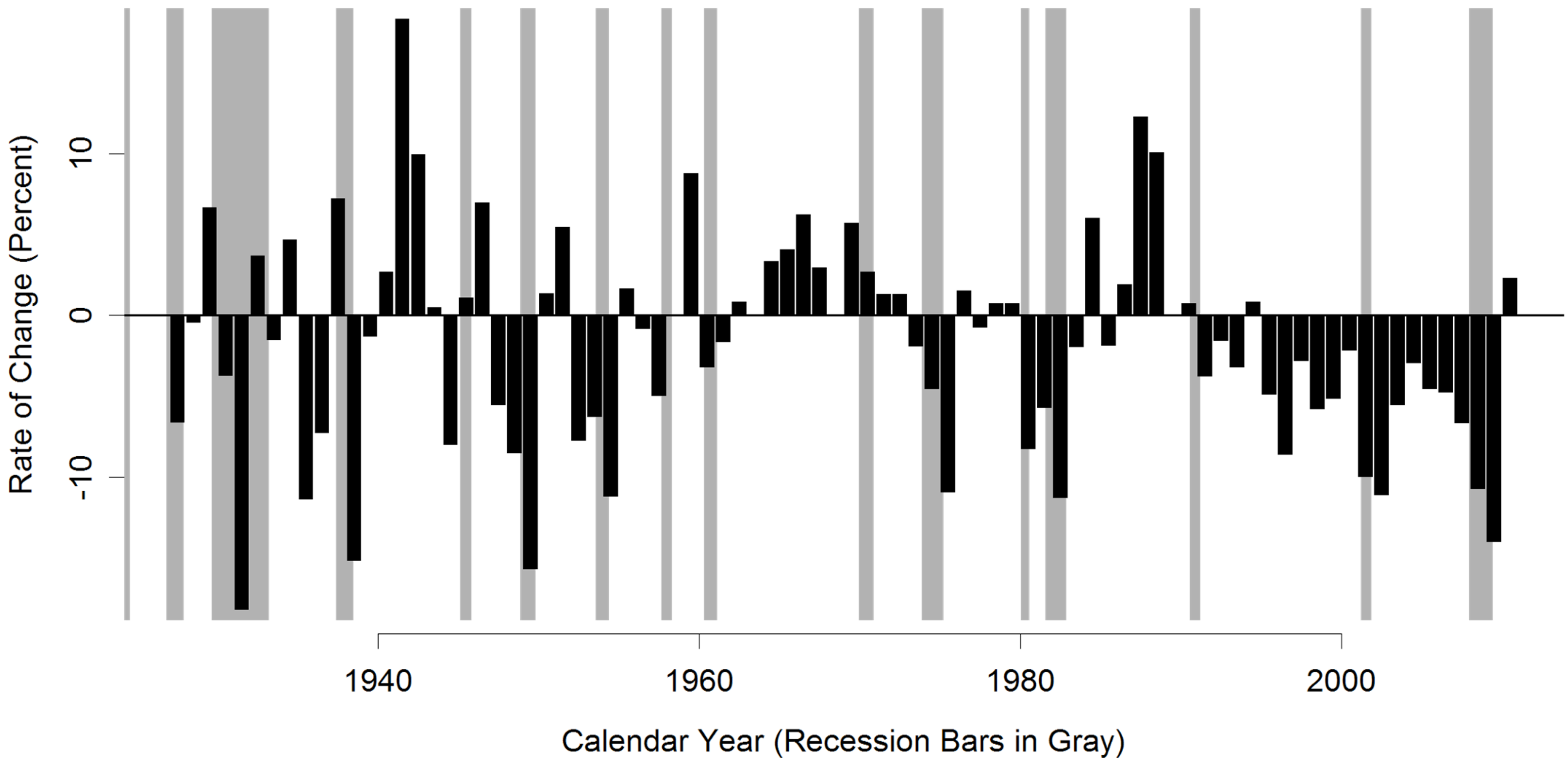
Manufacturing Injury and Illness Incidence Rate

Per 100 FTE Employees



The long series of manufacturing injury and illness rates (1926–2010) is inspired by research at the Federal Reserve Bank of Dallas. In its Annual Report, authored by Michael Cox and Richard Alm (dallasfed.org/assets/documents/fed/annual/2000/ar00.pdf), the Bank published a series of injury rates per 1,000 full-time workers in manufacturing for the period 1926 through 1999 (page 8).

Manufacturing Injury and Illness Incidence Rate
Log Growth Rate



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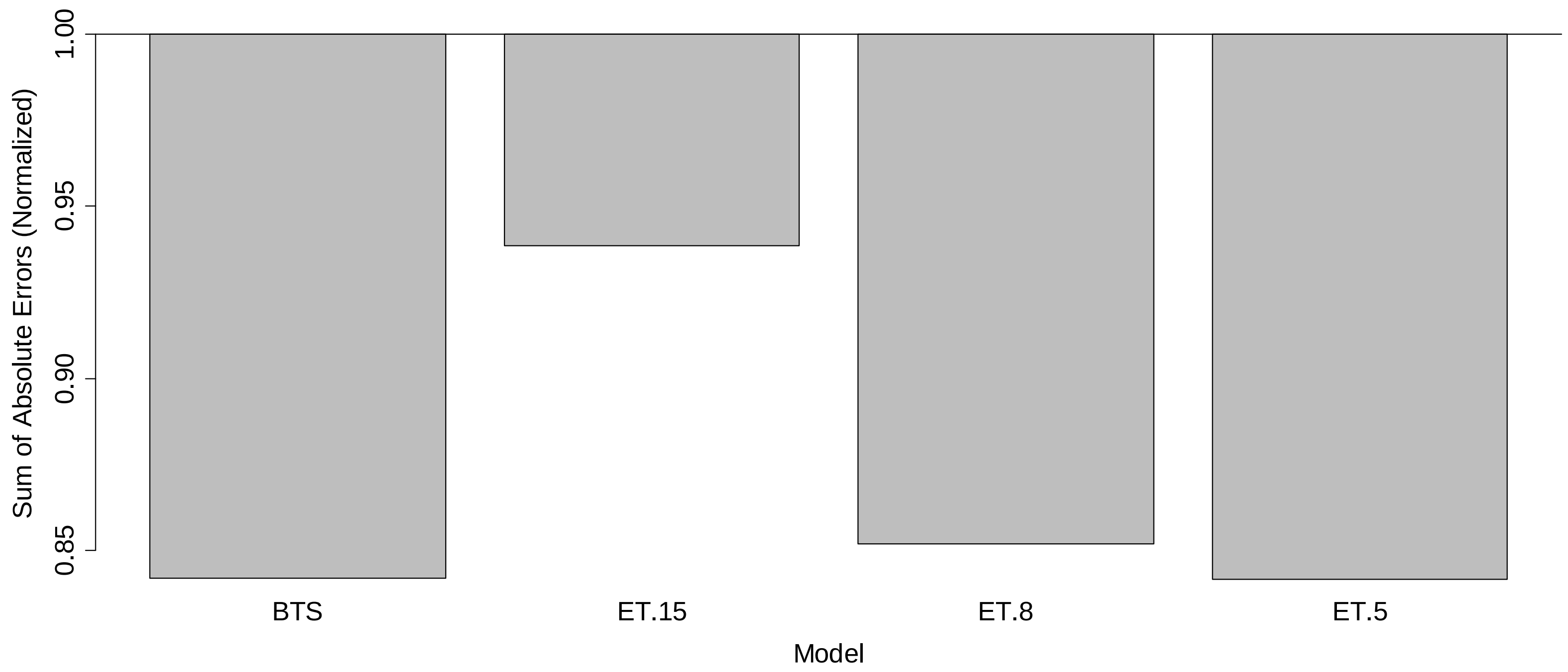
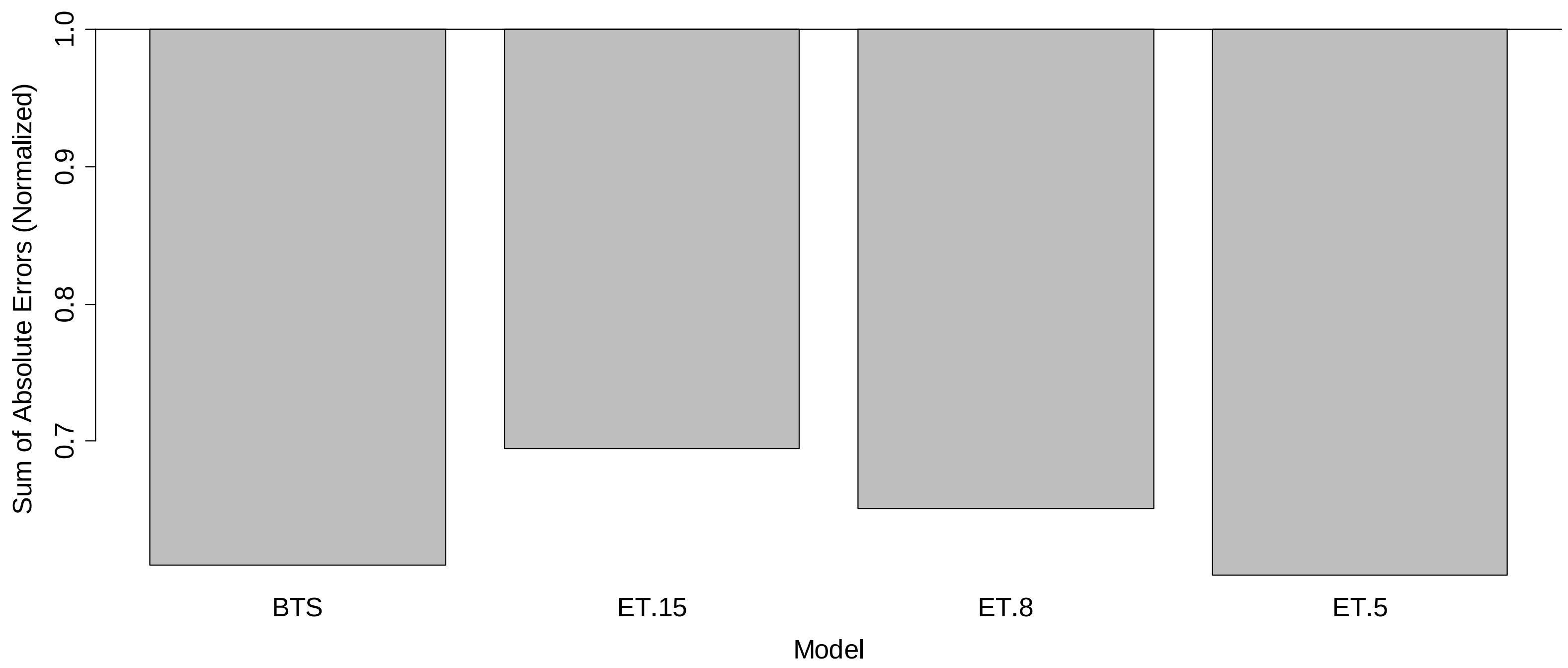
Manufacturing Injury and Illness Incidence Rate

Sum of Absolute Errors (1926–2010)



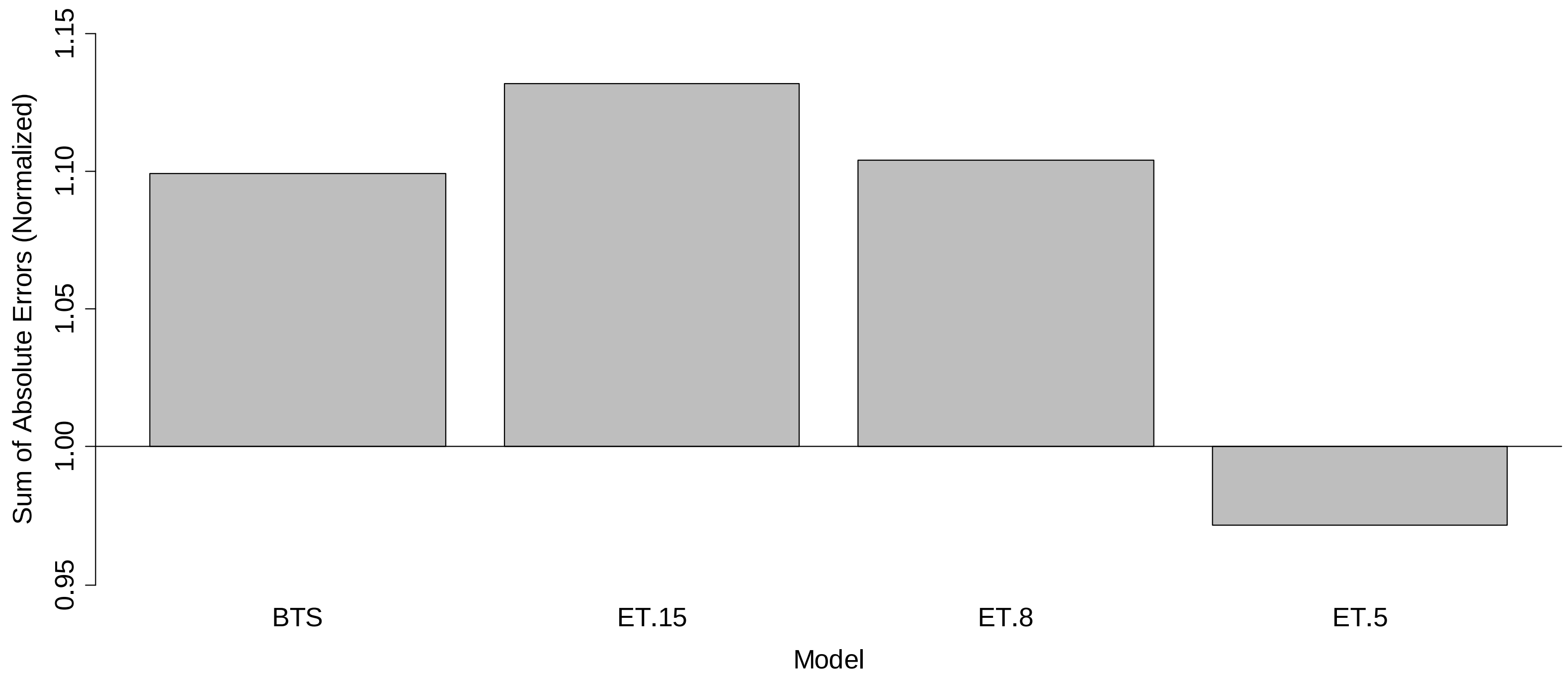
The values shown are normalized (i.e., divided) by the corresponding value associated with the random walk estimate

Manufacturing Injury and Illness Incidence Rate
Sum of Absolute Errors (1926–1964)



The values shown are normalized (i.e., divided) by the corresponding value associated with the random walk estimate

Manufacturing Injury and Illness Incidence Rate
Sum of Absolute Errors (1965–2010)



The values shown are normalized (i.e., divided) by the corresponding value associated with the random walk estimate

Conclusion

- The BTS objectively formalizes the trend selection process
  - Not subject to biases in human decision making
  - Not capable of processing information not incorporated in the data
- The BTS delivers a robust decision even as the nature of the time series changes