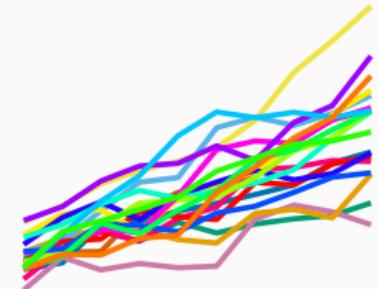


# Uncertain futures: what can we forecast and when should we give up?

Rob J Hyndman



[robjhyndman.com/uncertain\\_futures](http://robjhyndman.com/uncertain_futures)

# Outline

- 1 What can we forecast?
- 2 The statistical forecasting perspective
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# Reputations can be made and lost

“I think there is a world market for maybe five computers.”

(Chairman of IBM, 1943)

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(President, DEC, 1977)

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“We’re going to be opening relatively soon ... The virus ... will go away in April.”

(Donald Trump, February 2020)

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“We’re going to be opening relatively soon ... The virus ... will go away in April.”

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“We expect that Australians will be fully vaccinated by the end of October.”

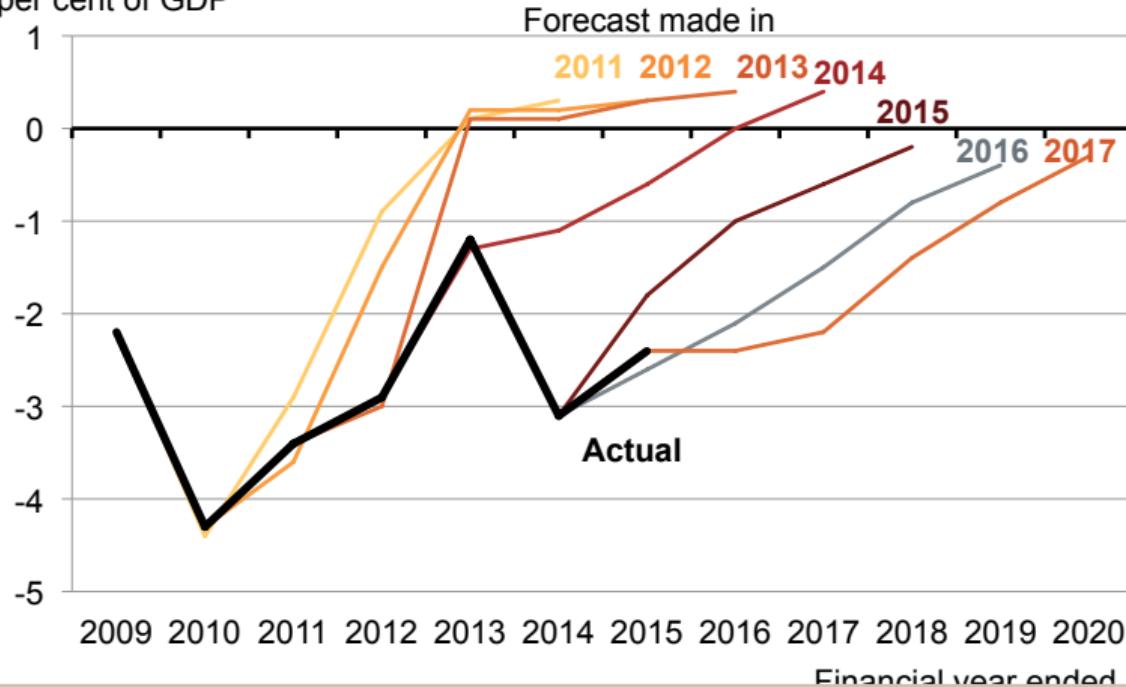
(Scott Morrison, December 2020)

# Forecasting is difficult

Commonwealth plans to drift back to surplus  
show the triumph of hope over experience

GRATTAN  
Institute

Actual and forecast Commonwealth underlying cash balance  
per cent of GDP



# What can we forecast?



# What can we forecast?



# What can we forecast?



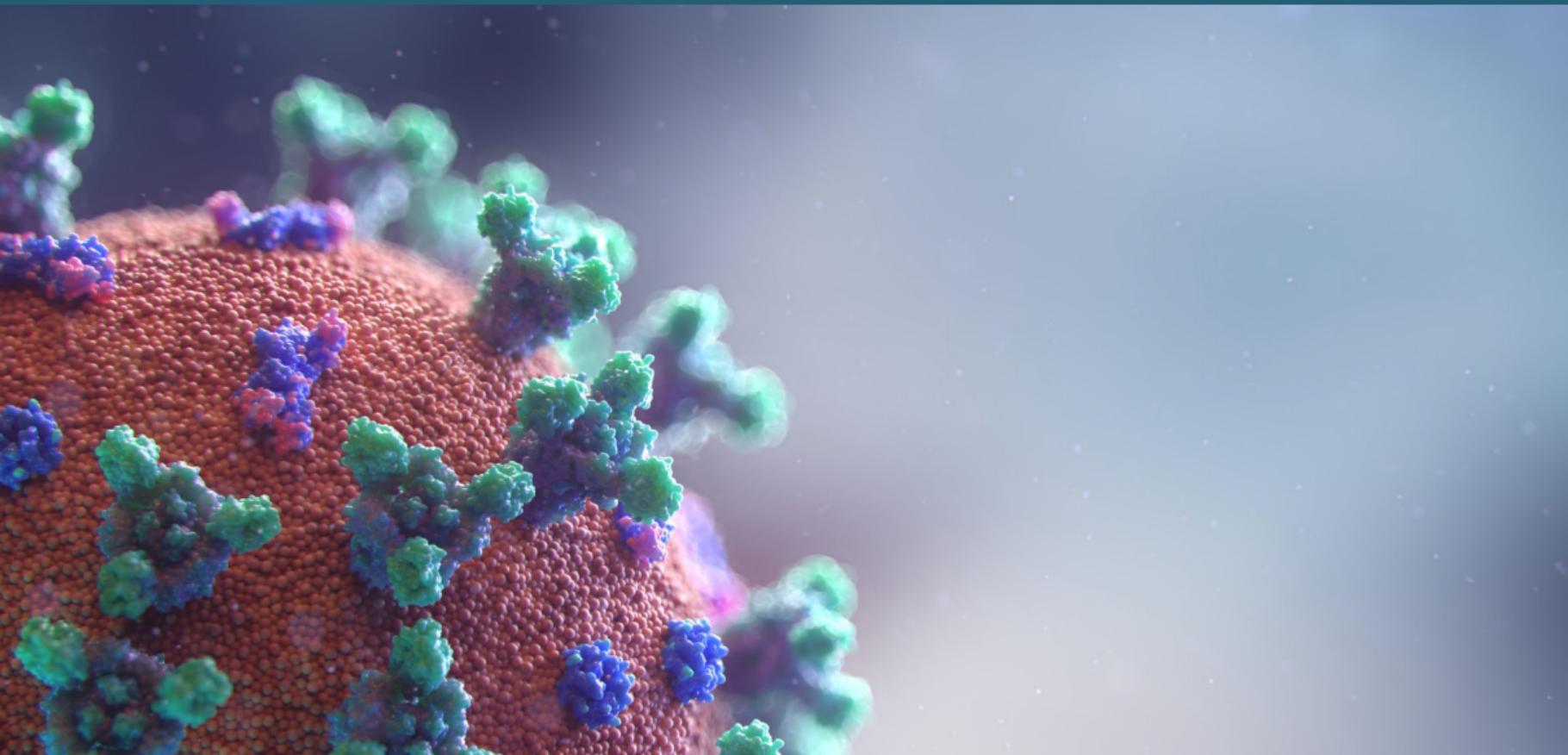
# What can we forecast?



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# What can we forecast?



# What can we forecast?



# Which is easiest to forecast?

- daily electricity demand in 3 days time
- timing of next Halley's comet appearance
- time of sunrise this day next year
- Google stock price tomorrow
- Google stock price in 6 months time
- maximum temperature tomorrow
- exchange rate of \$US/AUS next week
- total sales of drugs in Australian pharmacies next month

# Which is easiest to forecast?

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# Which is easiest to forecast?

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- how do we measure “easiest”?
  - what makes something easy/difficult to forecast?

# Forecastability factors

Something is easier to forecast if:

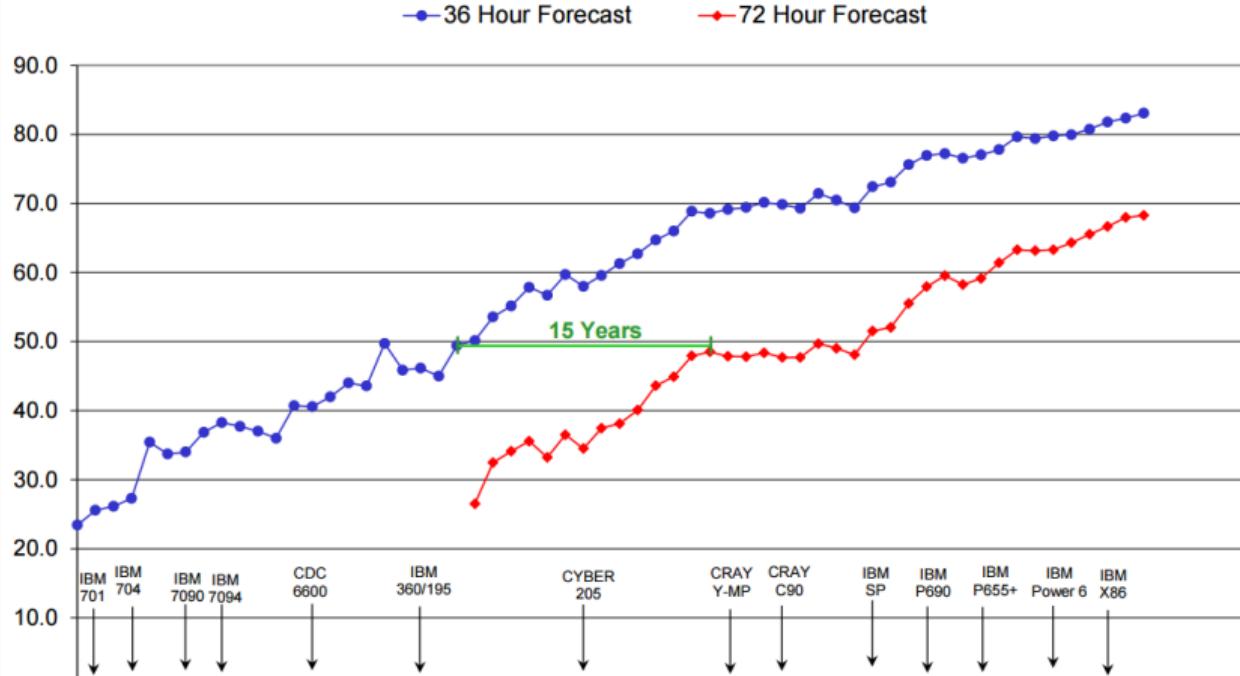
- 1 we have a good understanding of the factors that contribute to it
- 2 there is lots of data available;
- 3 the future is somewhat similar to the past
- 4 the forecasts cannot affect the thing we are trying to forecast.

# Improving forecasts



## NCEP Operational Forecast Skill

36 and 72 Hour Forecasts @ 500 MB over North America  
[ $100 * (1 - S1/70)$  Method]



# Outline

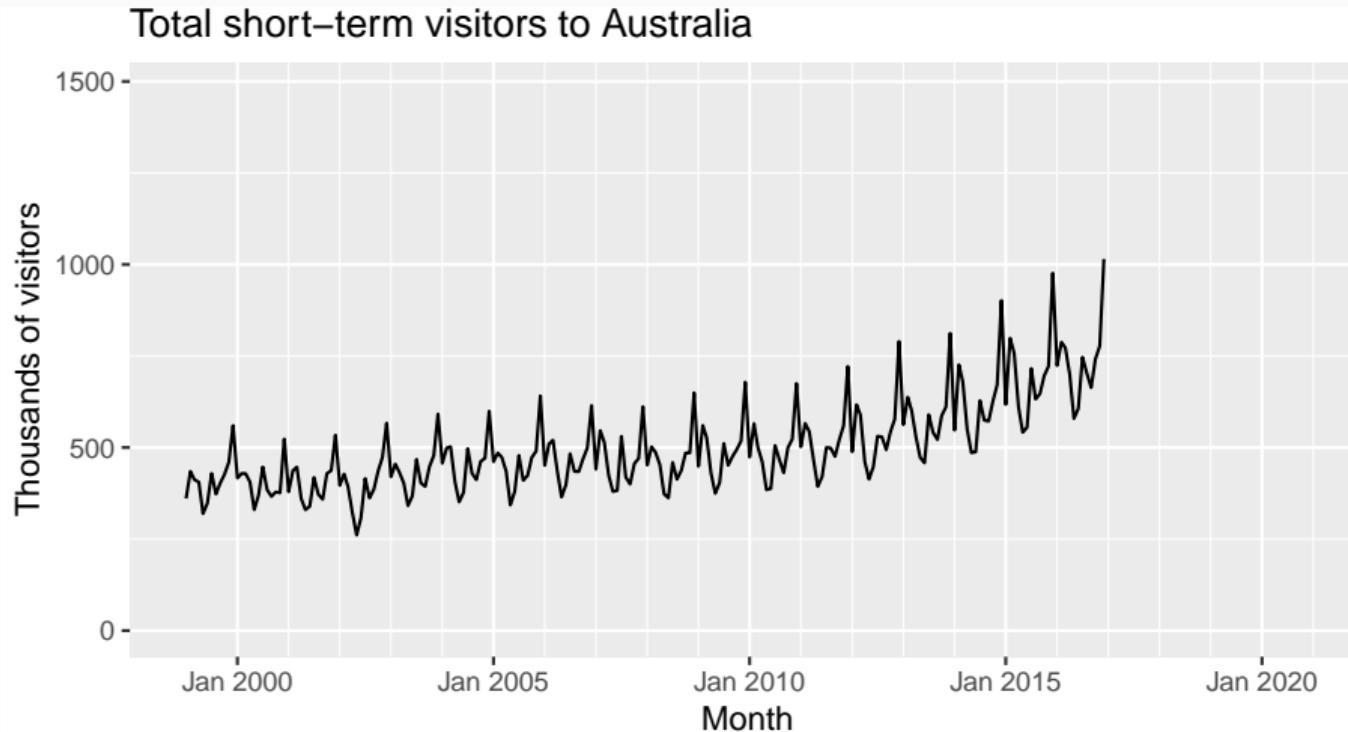
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# Random futures

A forecast is an estimate of the probability distribution of a variable to be observed in the future.

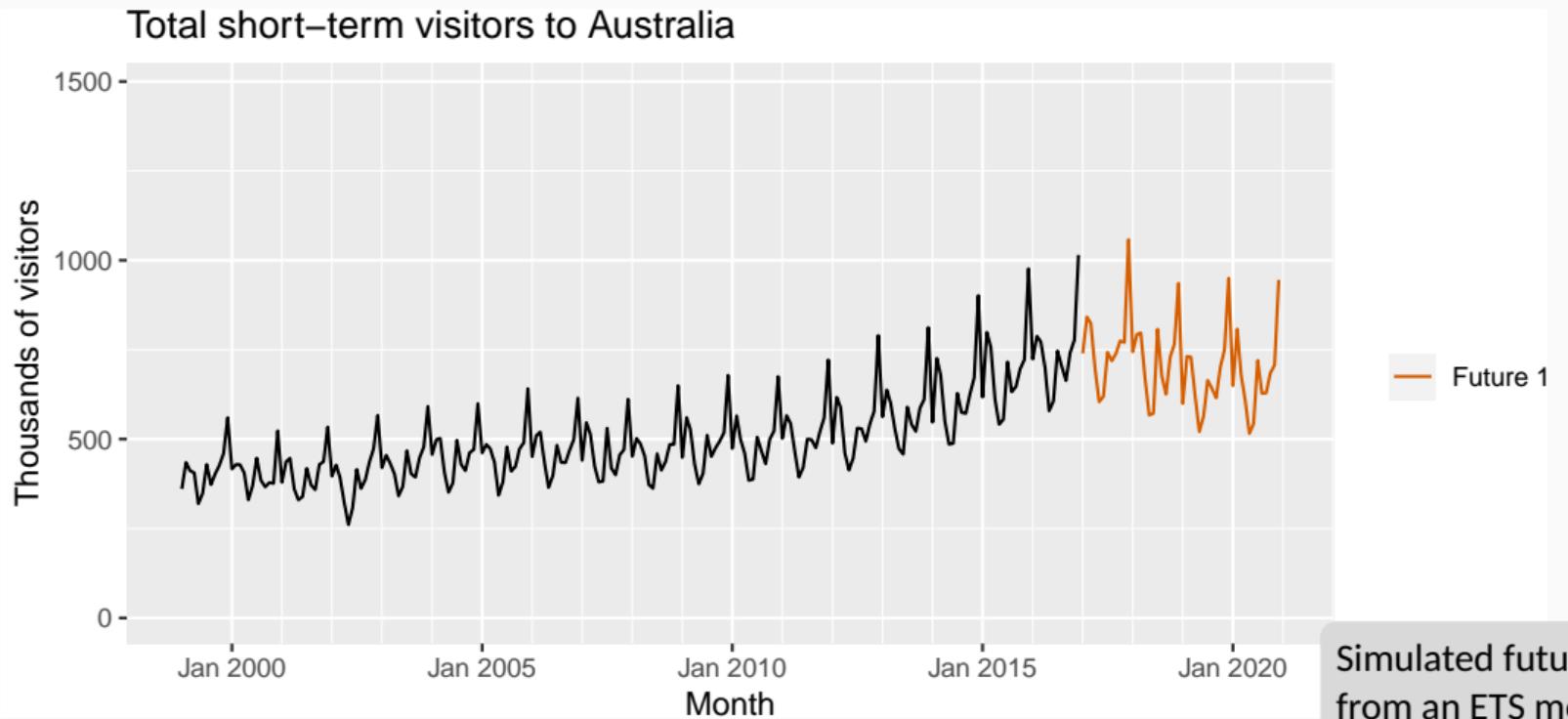
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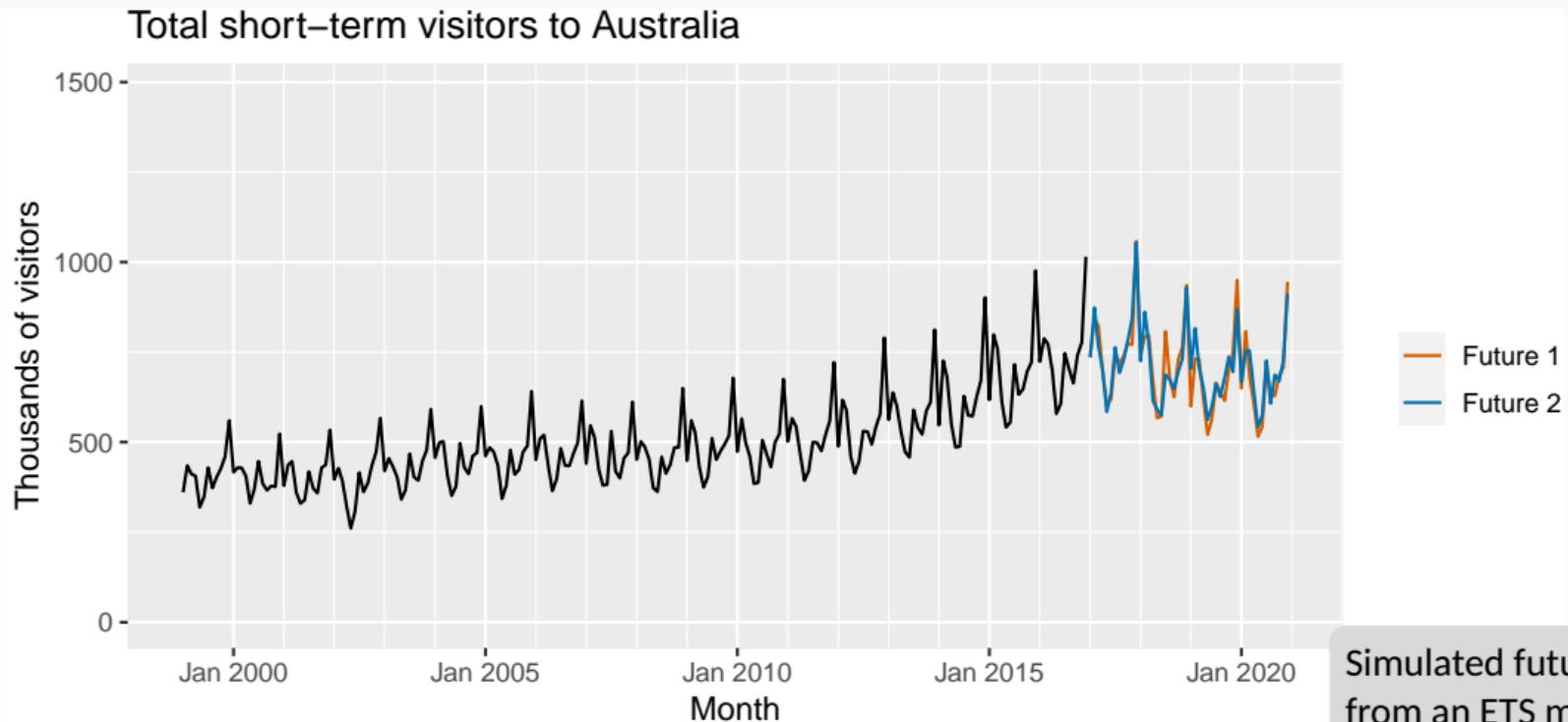
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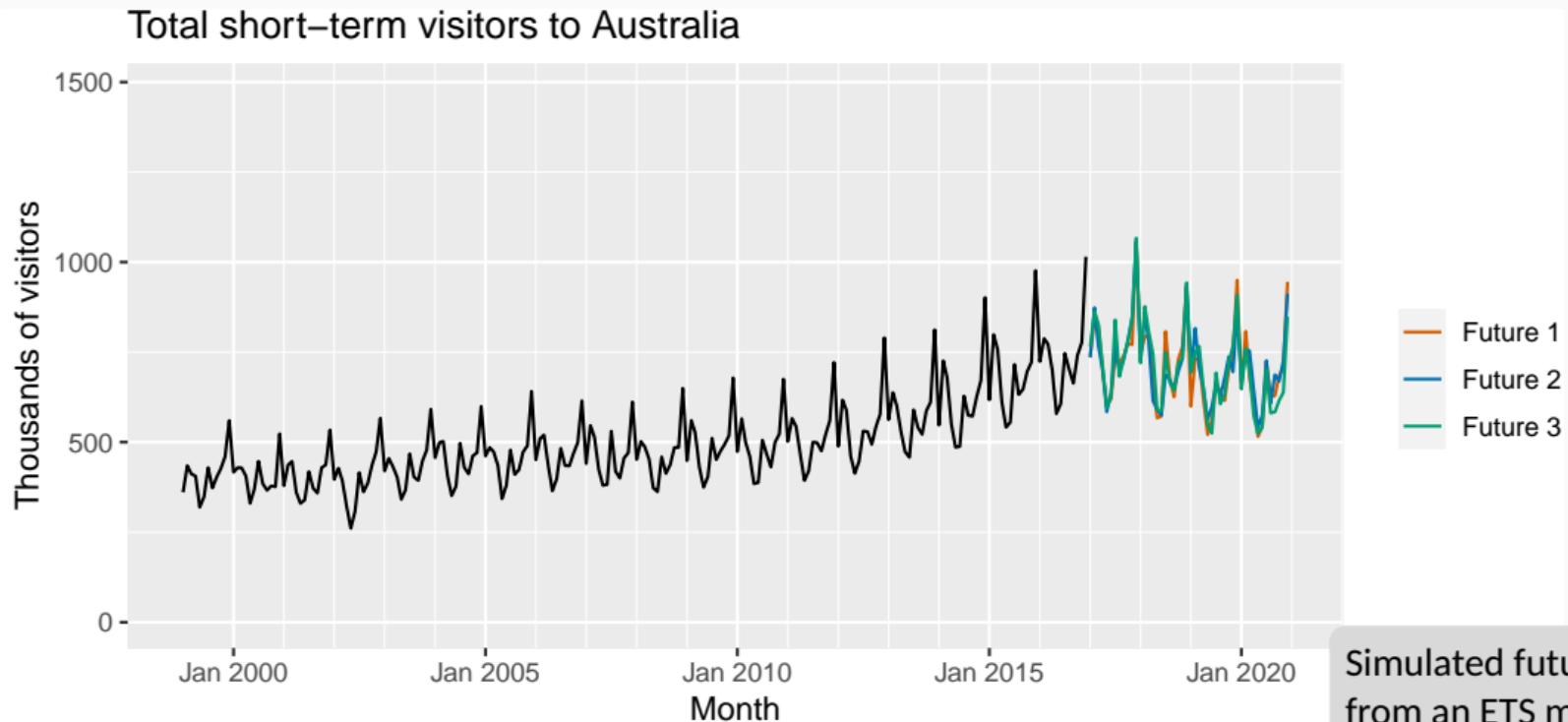
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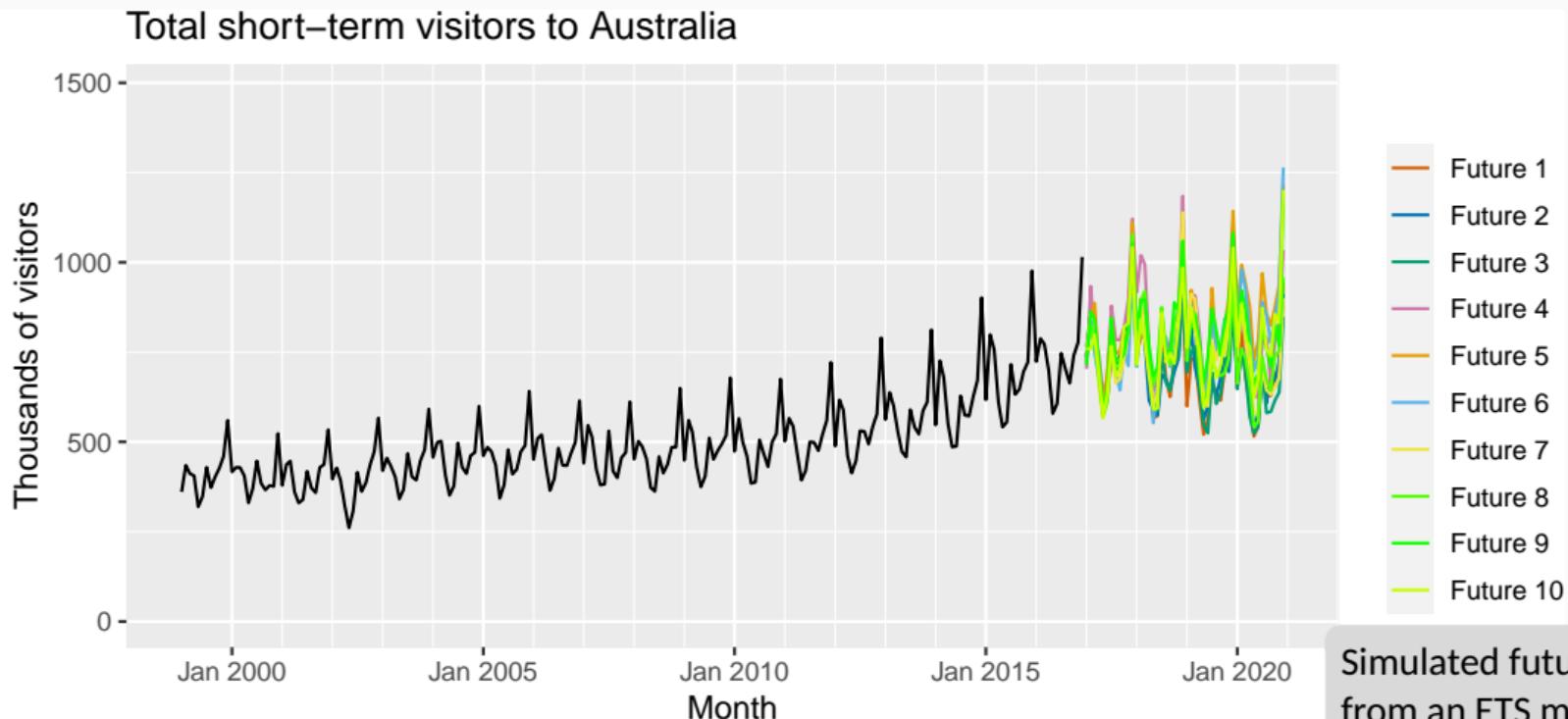
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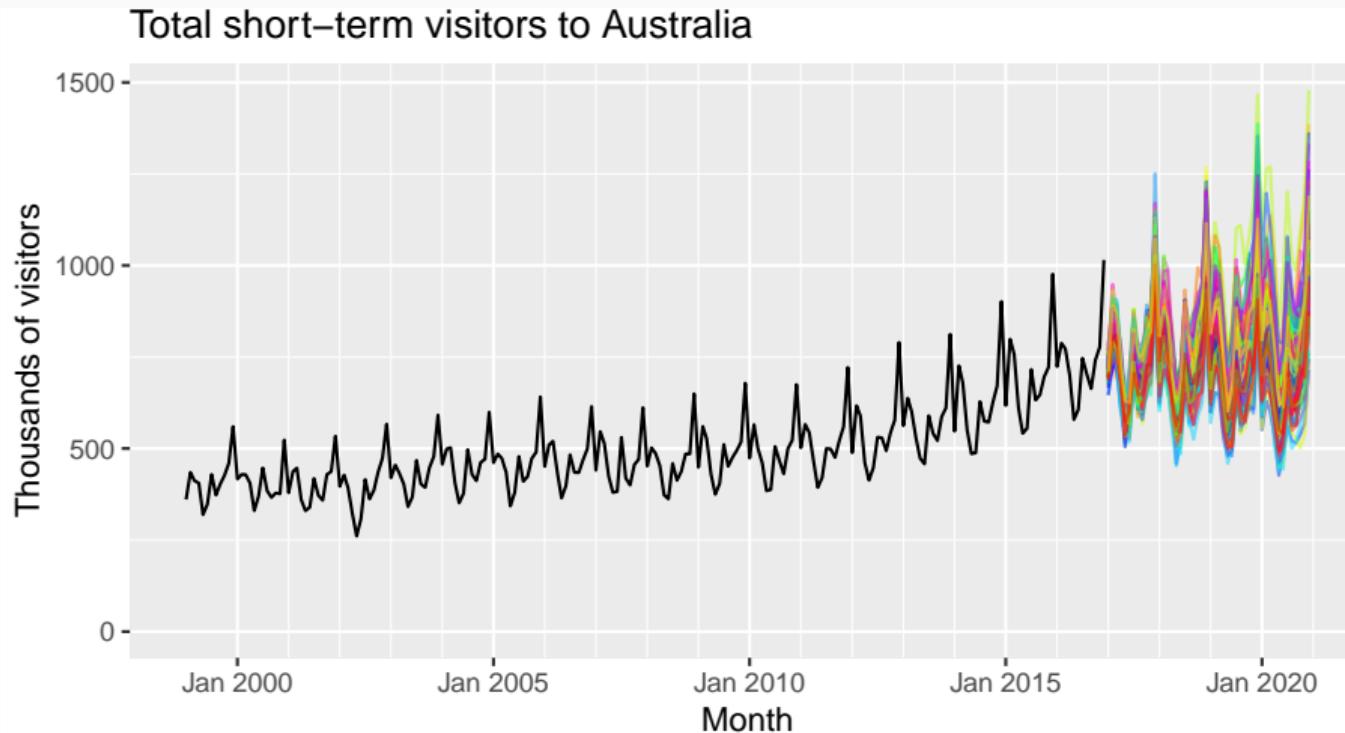
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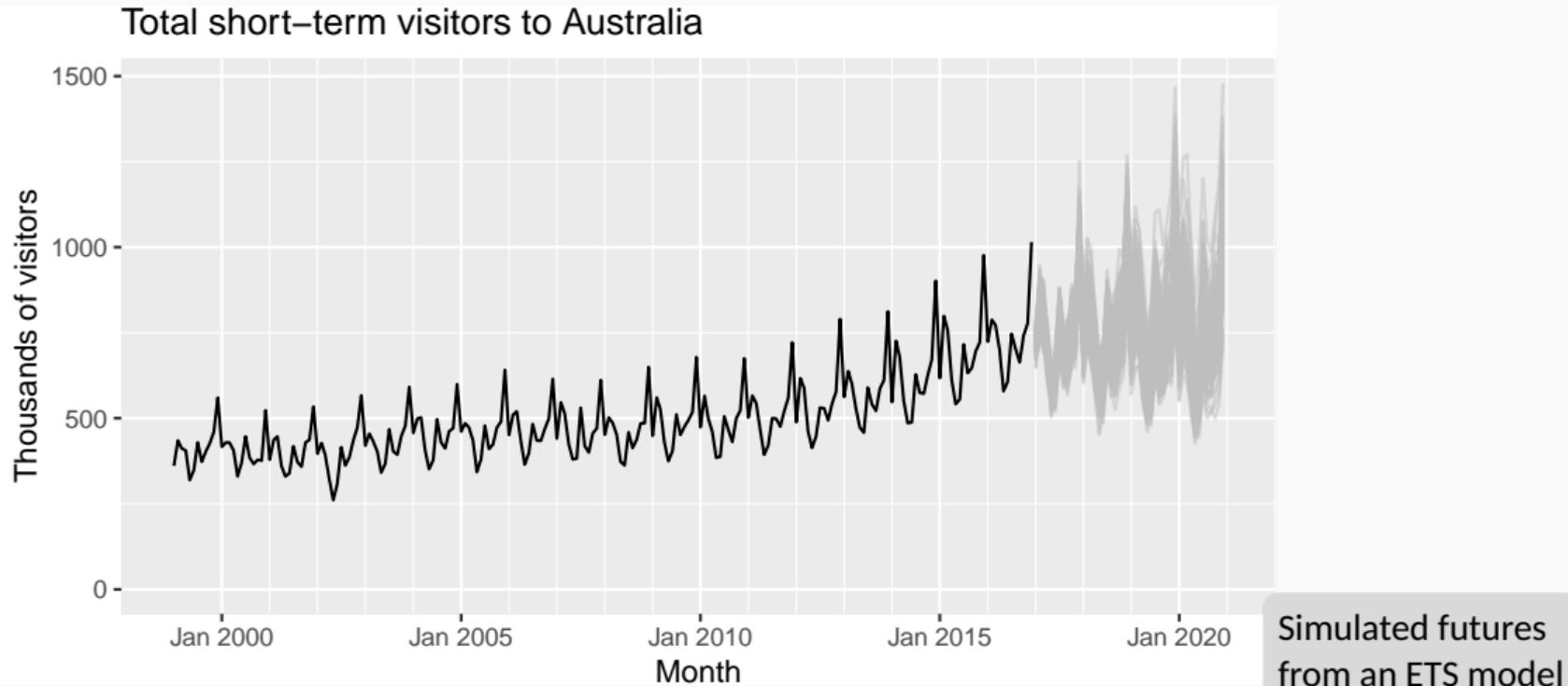
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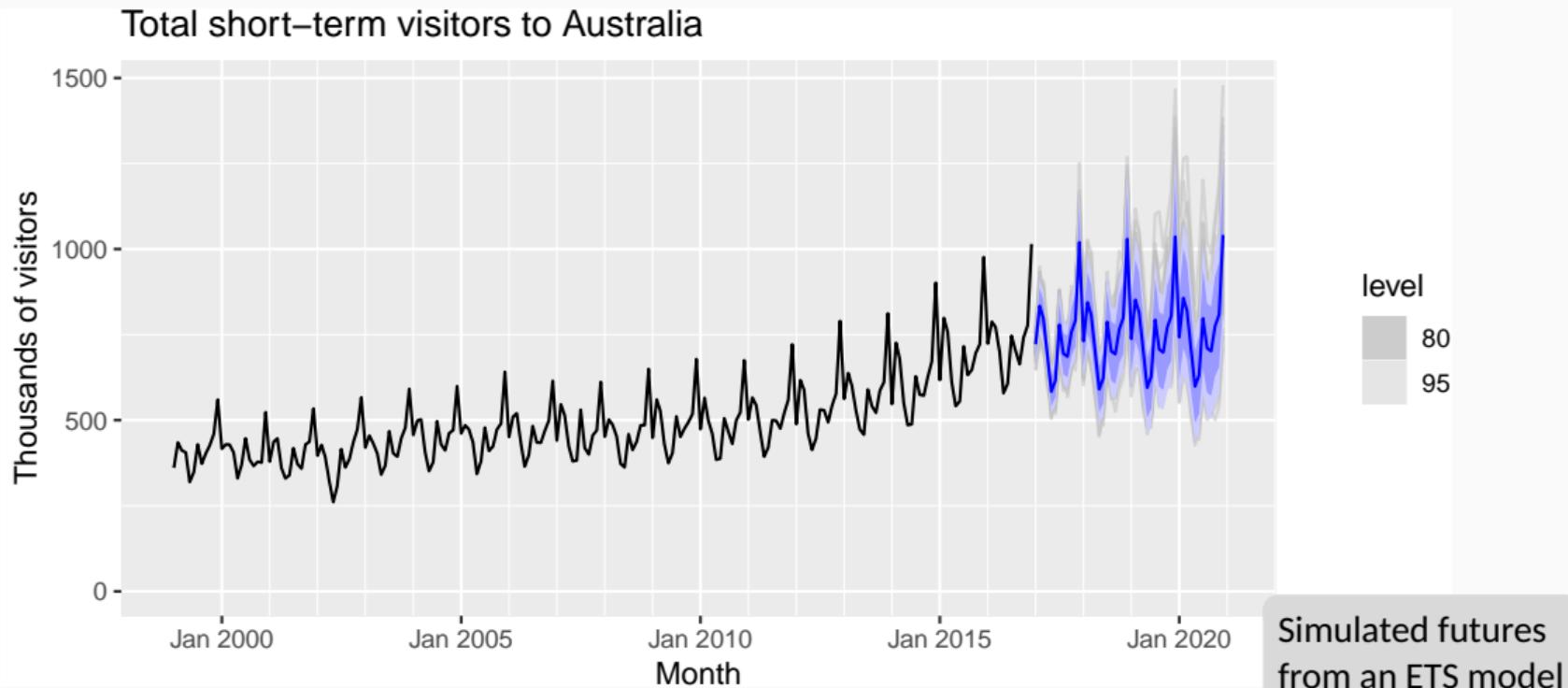
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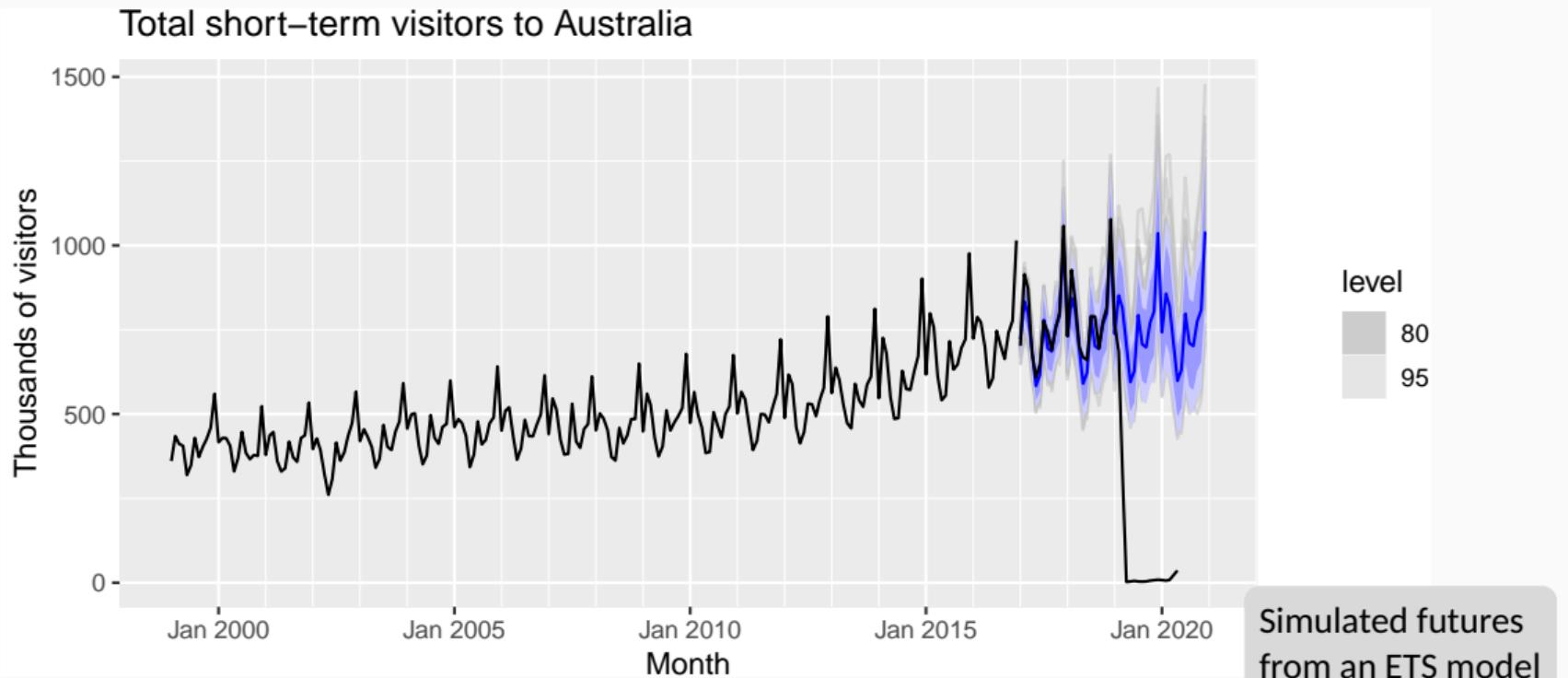
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# Forecasting PBS expenditure



# Forecasting PBS expenditure

**The Pharmaceutical Benefits Scheme (PBS) is the Australian government drugs subsidy scheme.**

- Many drugs bought from pharmacies are subsidised to allow more equitable access to modern drugs.
- The cost to government is determined by the number and types of drugs purchased. Currently nearly 1% of GDP.
- The total cost is budgeted based on forecasts of drug usage.

# Forecasting PBS expenditure

**ABC News Online**  
AUSTRALIAN BROADCASTING CORPORATION

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POLITICS

## Opp demands drug price restriction after PBS budget blow-out

The Federal Opposition has called for tighter controls on drug prices after the Pharmaceutical Benefits Scheme (PBS) budget blew out by almost \$800 million.

The money was spent on two new drugs including the controversial anti-smoking aid Zyban, which dropped in price from \$220 to \$22 after it was listed on the

Windows Media NewsRadio Streaming audio news  
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This Bulletin: Wed, May 30 2001 6:22 PM AEST

**the Public Record**  
For full election coverage

**FEATURES**

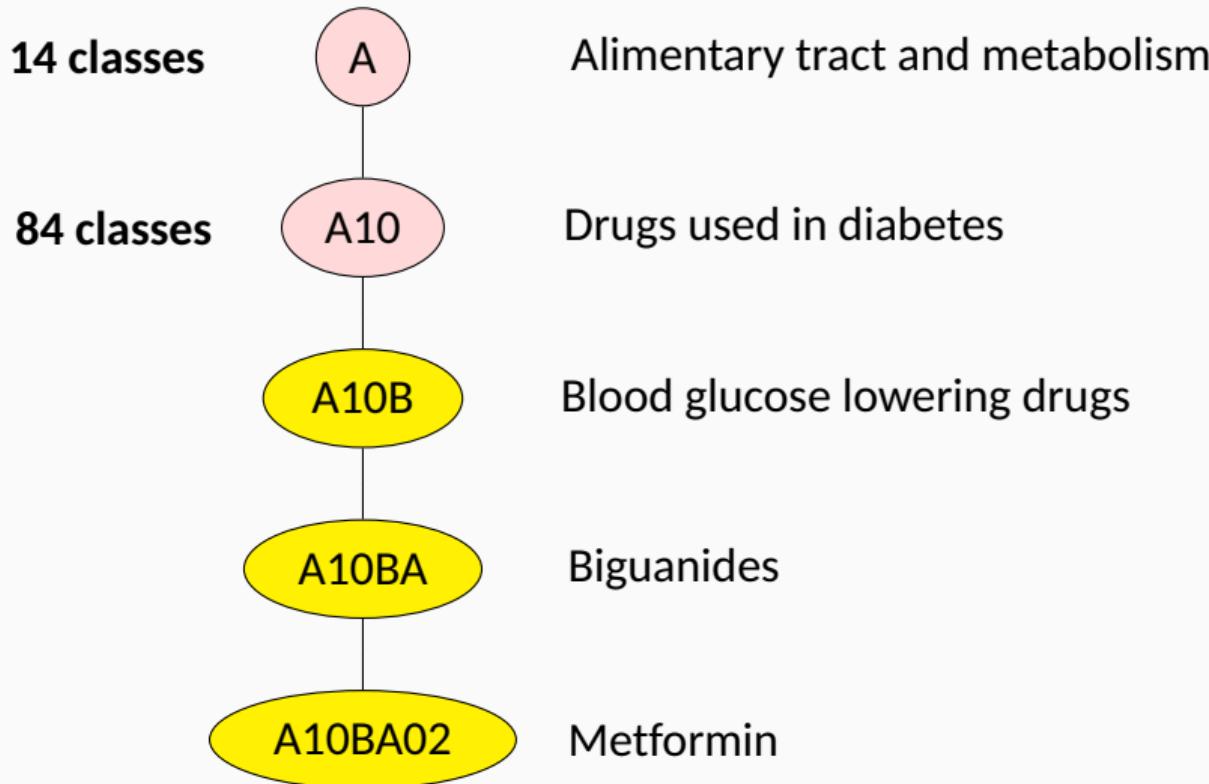
**Public Record**  
Federal Election 2001

For a fresh perspective on the federal election, reach into ABC Online's campaign weblog, [The Poll Vault](#).

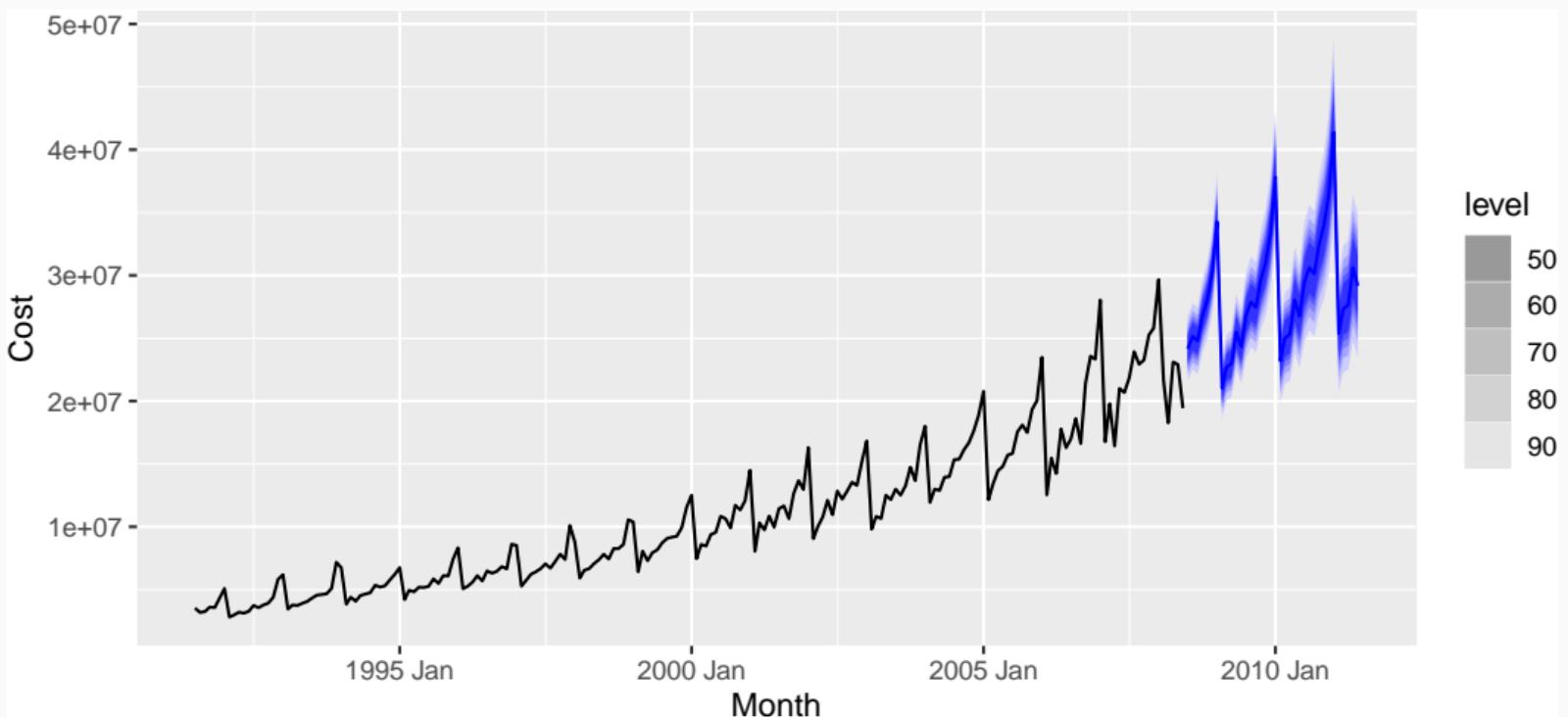
# Forecasting PBS expenditure

- In 2001: \$4.5 billion budget, under-forecasted by \$800 million.
- Thousands of products. Seasonal demand.
- Subject to covert marketing, volatile products, uncontrollable expenditure.
- Although monthly data available for 10 years, data are aggregated to annual values, and only the first three years are used in estimating the forecasts.
- All forecasts being done with the FORECAST function in MS-Excel!

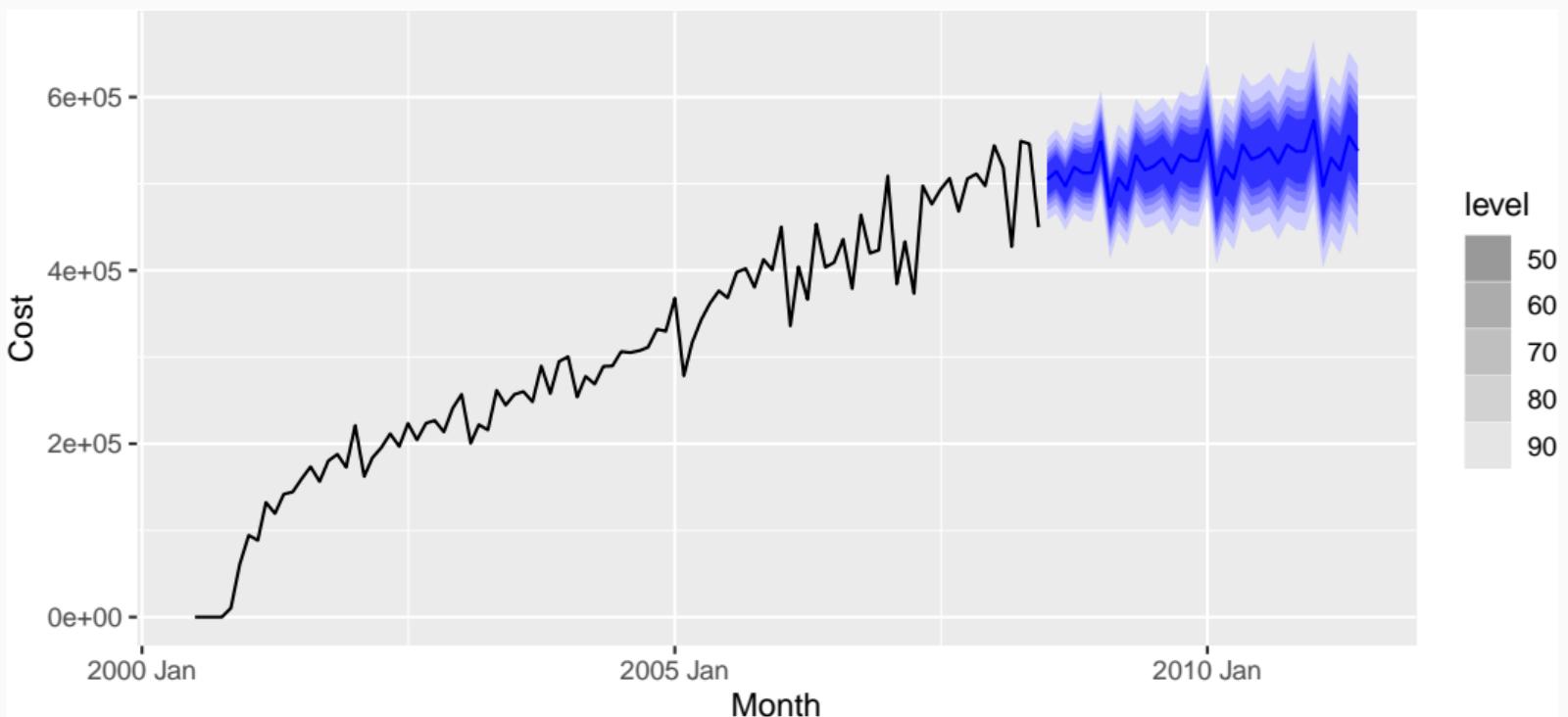
# ATC drug classification



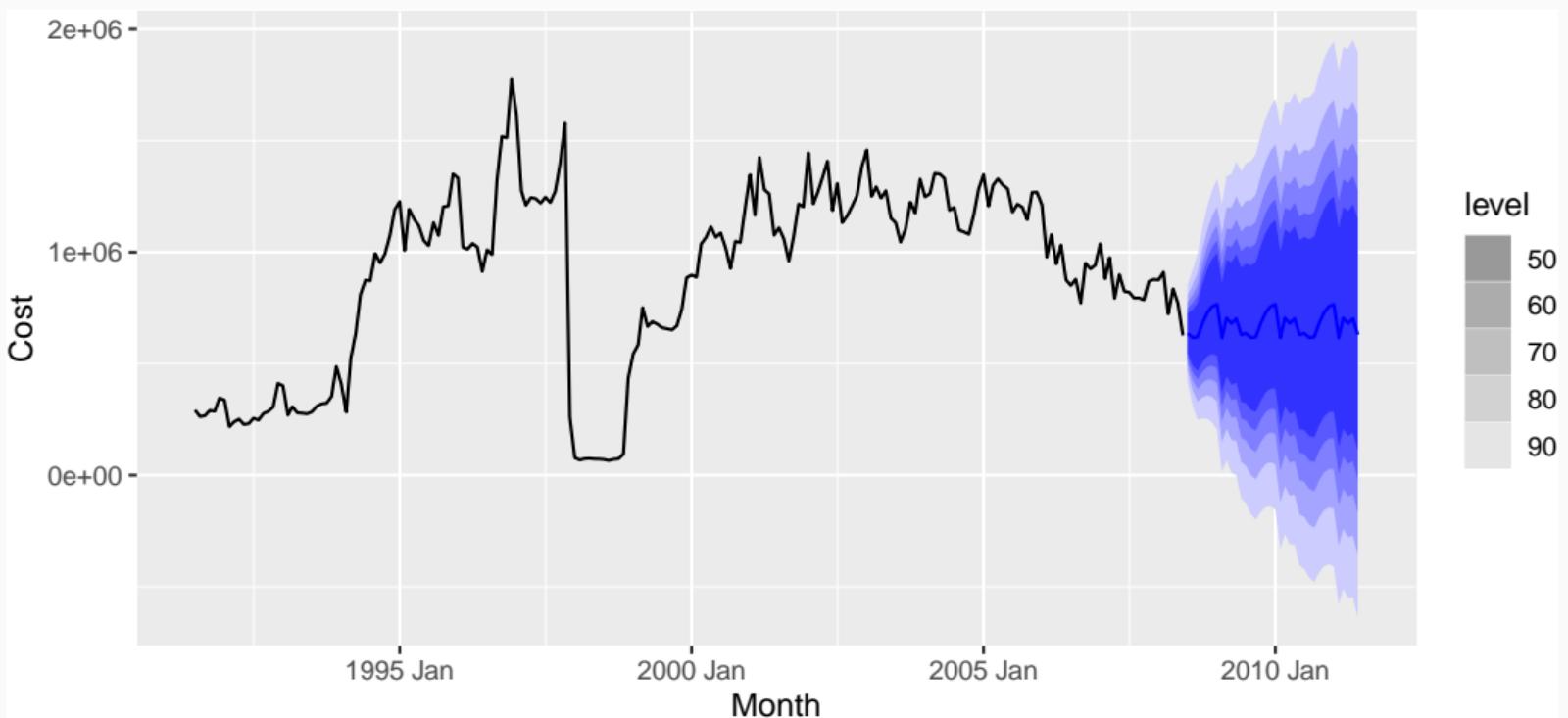
# ETS forecasts of PBS data



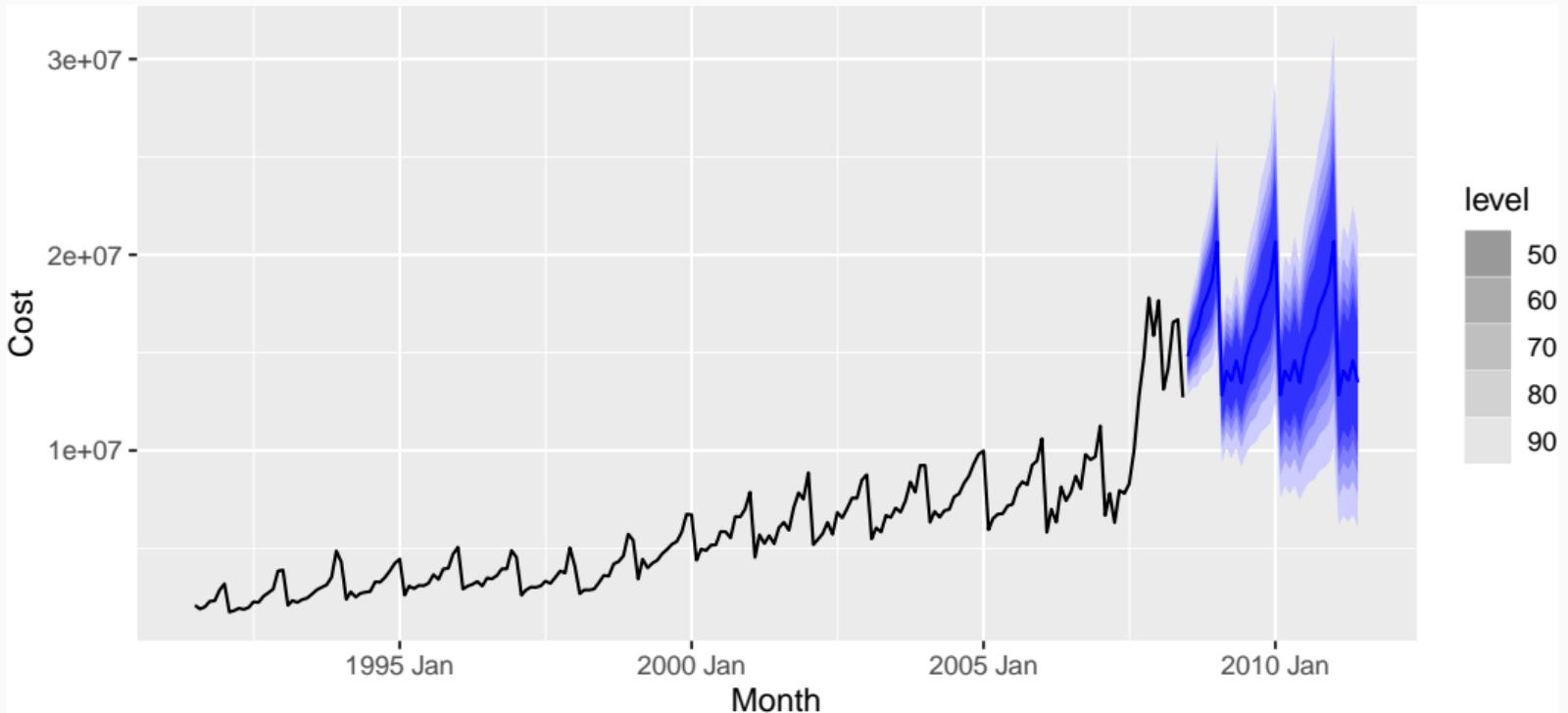
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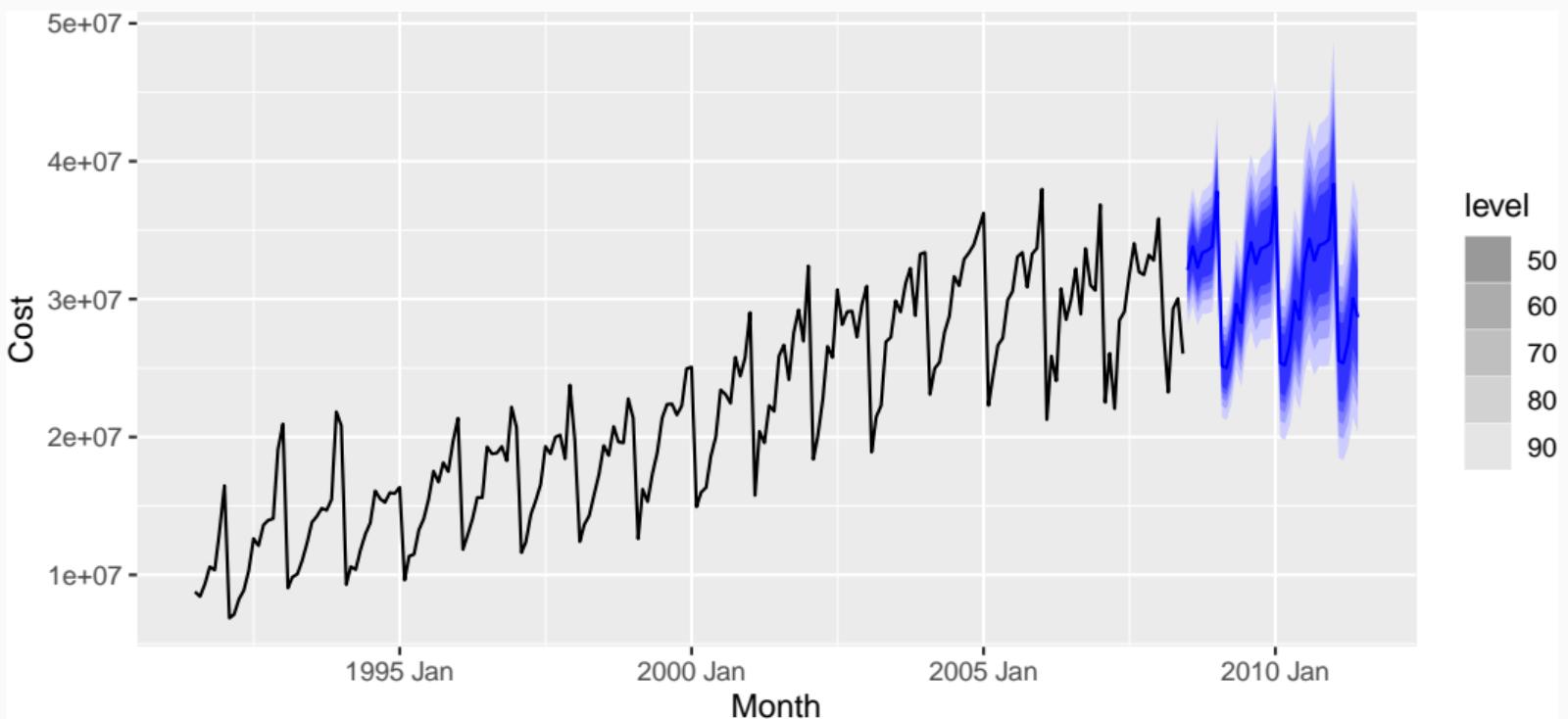
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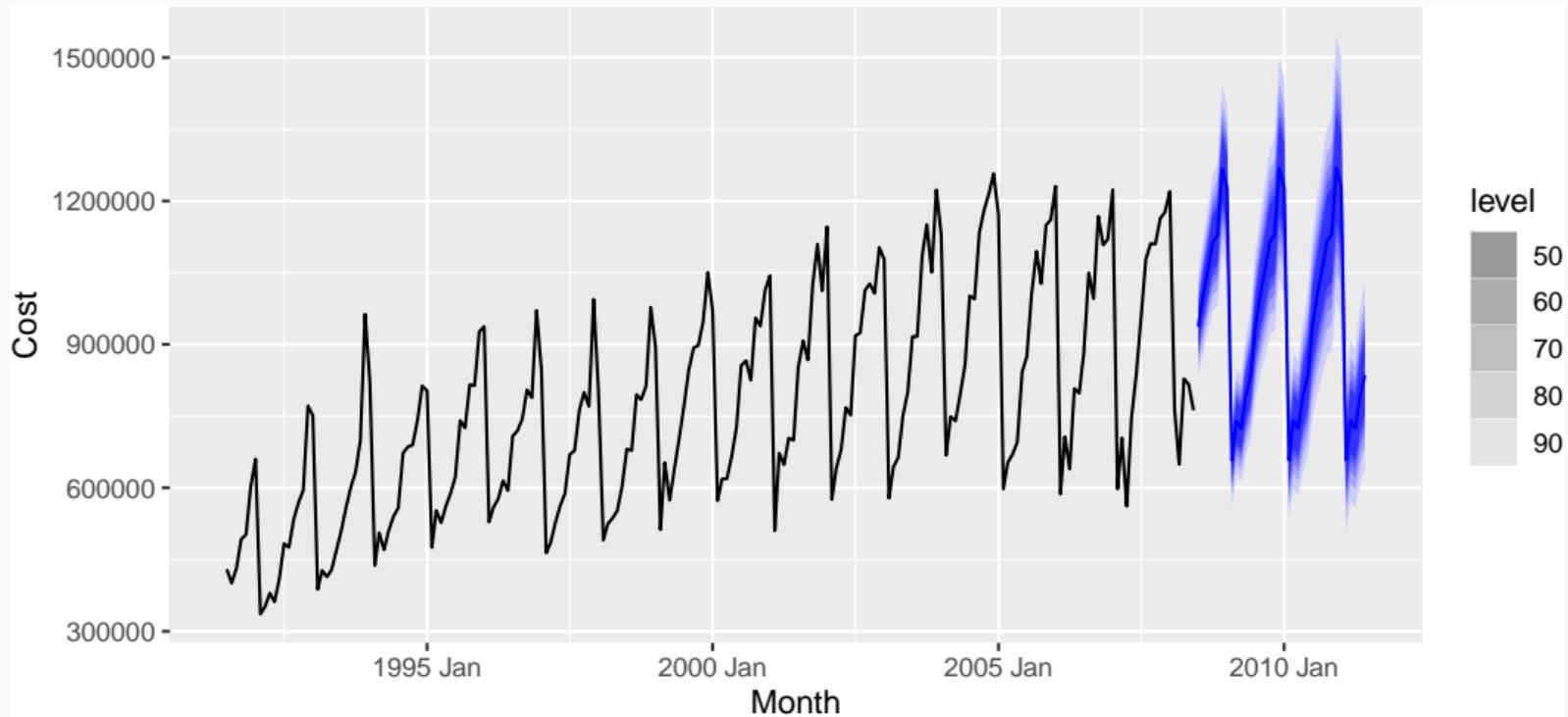
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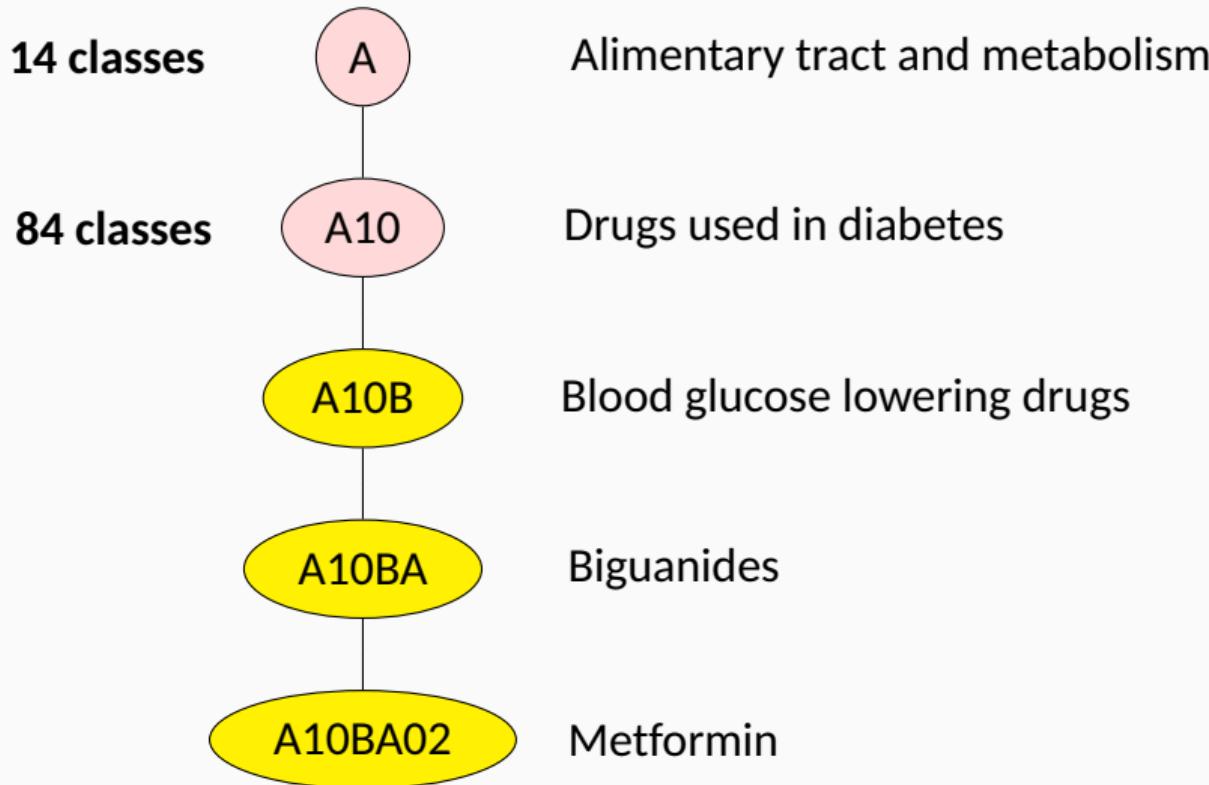
# ETS forecasts of PBS data



# Forecasting PBS expenditure

- Developed an automatic forecasting algorithm for exponential smoothing state space models based on the AIC.
- Exponential smoothing models allowed for time-changing trend and seasonal patterns.
- Forecast MAPE reduced from 15–20% to 0.6%.
- State space models provide prediction intervals which give a sense of uncertainty.
- Theory and algorithm published as Hyndman et al (IJF, 2002).
- Now implemented in R as `ets()` in `forecast` package, as `ETS()` function in `fable` package, and in Tableau and elsewhere.
- NOT implemented in FORECAST.ETS function in MS-Excel.

# Hierarchical forecasting



# Hierarchical forecasting

- Nearly ten years later, Hyndman et al (CSDA, 2011) proposed forecast reconciliation to handle hierarchical time series.
- Now widely used in business and industry and implemented in the `hts` and `fable` packages.

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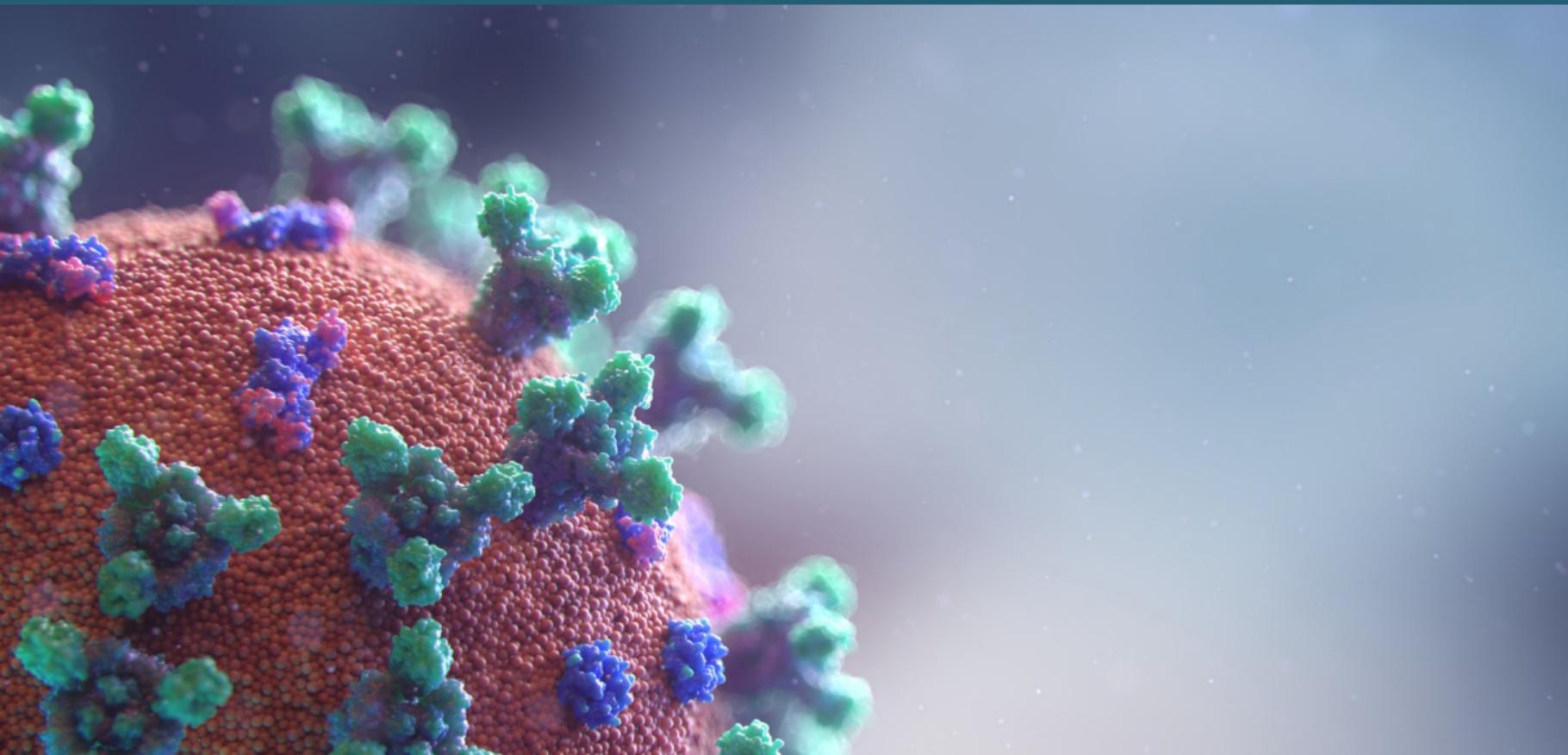
# Forecasting peak electricity demand



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# Forecasting COVID19 cases



# Data sources

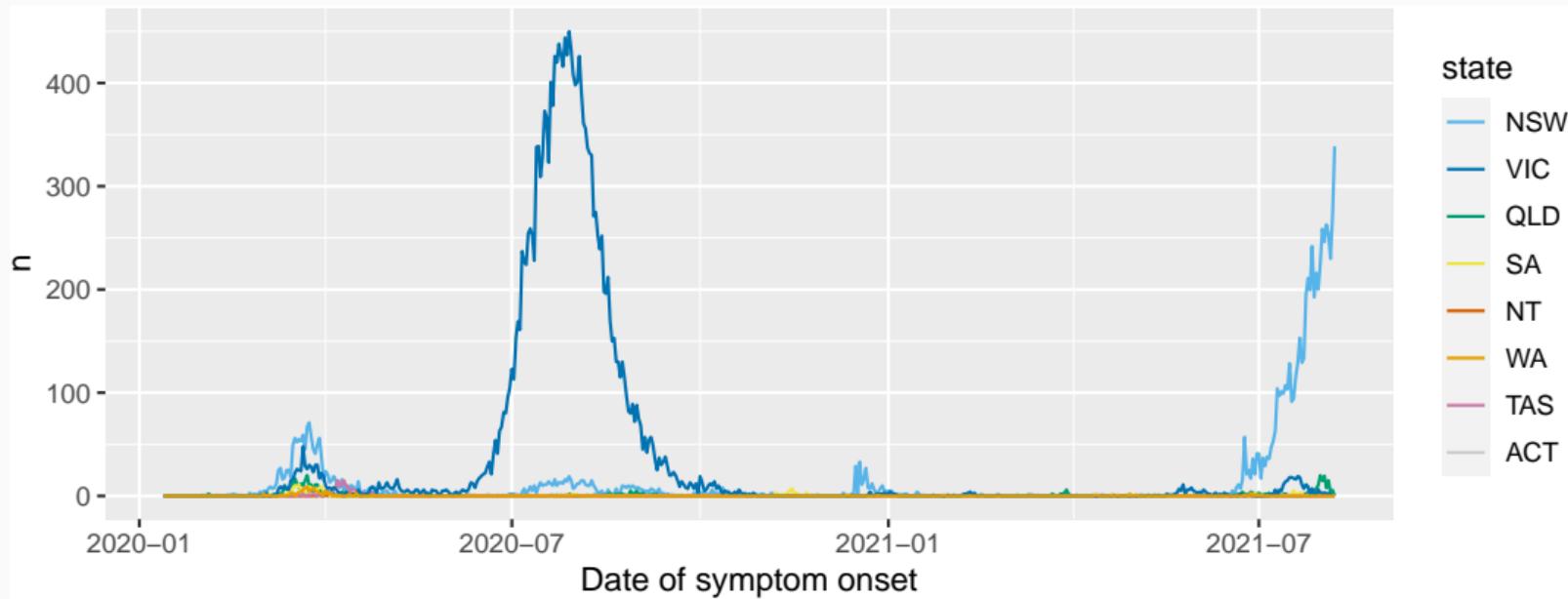
- Case-level data of all positive COVID-19 tests: onset and detection times.
- Daily population mobility data from Google, Apple & Facebook
- Weekly non-household contact surveys
- Weekly behavioural surveys
- Daily case numbers from many countries and regions via the Johns Hopkins COVID-19 repository

# Case numbers

```
localcases %>% filter(state == "VIC", date >= "2020-07-01")
```

```
## # A tsibble: 402 x 3 [1D]
## # Key:       state [1]
##   date       state     n
##   <date>     <chr> <dbl>
## 1 2020-07-01 VIC     123
## 2 2020-07-02 VIC     113
## 3 2020-07-03 VIC     153
## 4 2020-07-04 VIC     169
## 5 2020-07-05 VIC     161
## 6 2020-07-06 VIC     237
## 7 2020-07-07 VIC     227
## 8 2020-07-08 VIC     224
## 9 2020-07-09 VIC     254
```

# Case numbers



- Recent case numbers are uncertain and incomplete as date of onset is not known until symptoms show and a test is obtained.

# Global daily cases by region from Johns Hopkins

<https://github.com/CSSEGISandData/COVID-19>



# A model ensemble

## Model 1: SEIIR (Uni Melbourne/Doherty Institute)

- Stochastic compartmental model with time-varying effective reproduction number.

## Model 2: Generative model (Uni Adelaide)

- Simulation with three types of infectious individuals: imported, asymptomatic, symptomatic

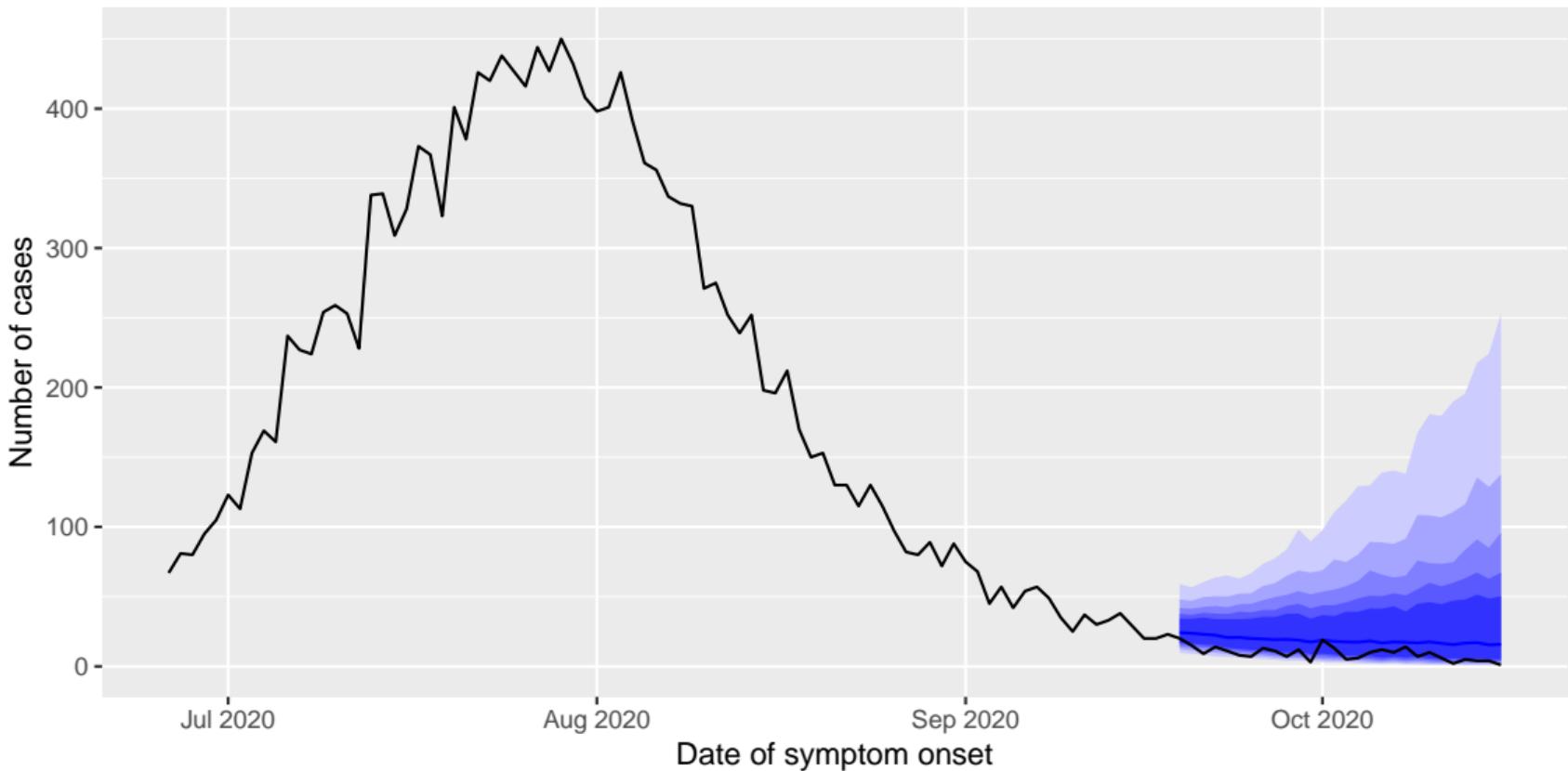
## Model 3: Global AR model (Monash)

- Single model fitted to all Johns Hopkins data from countries and regions with sufficient data.
- Series with obvious anomalies removed.

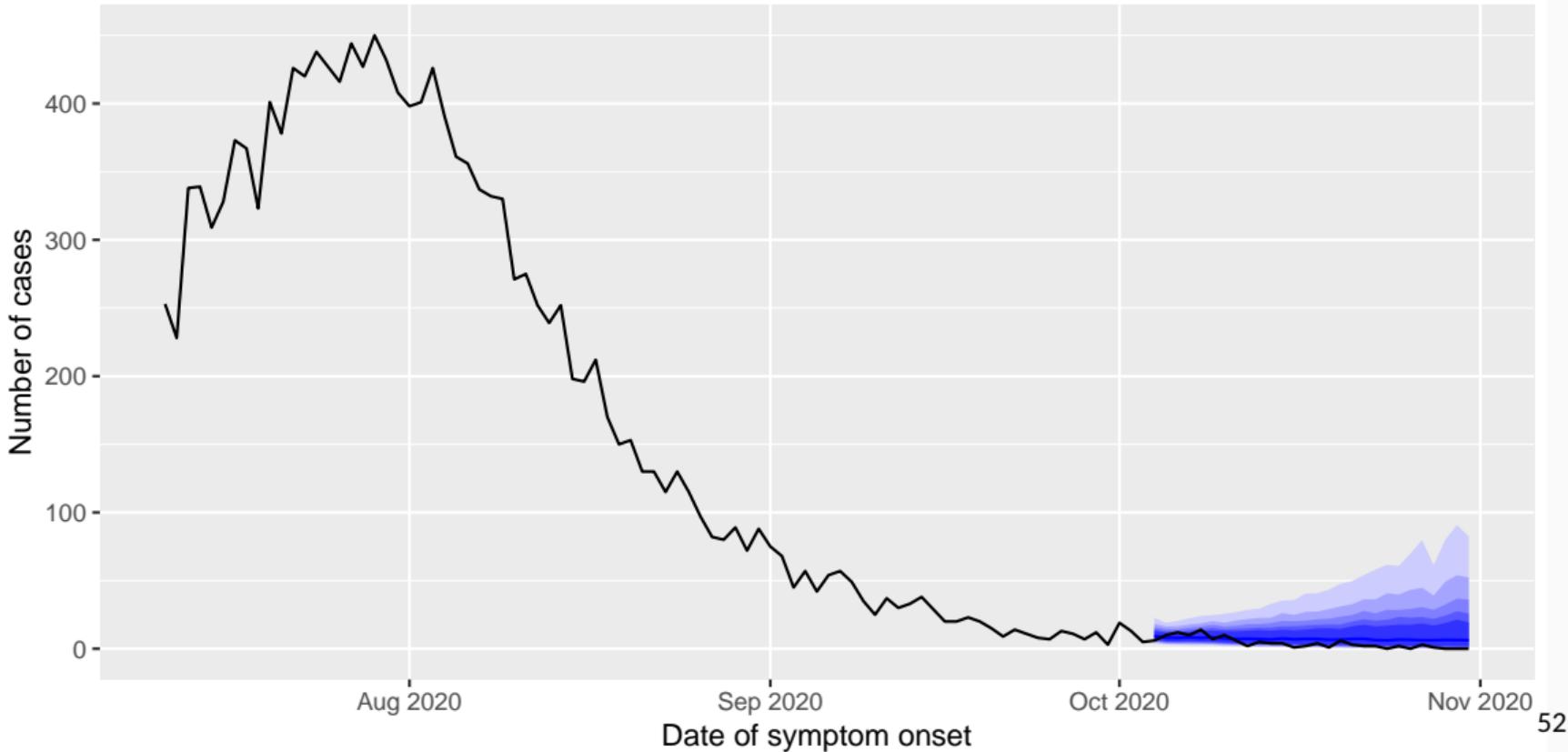
# Forecasting ensemble

- Forecasts obtained from a equally-weighted mixture distribution of the component forecasts.
- Also known as “linear pooling”
- Works best when individual models are over-confident and use different data sources.

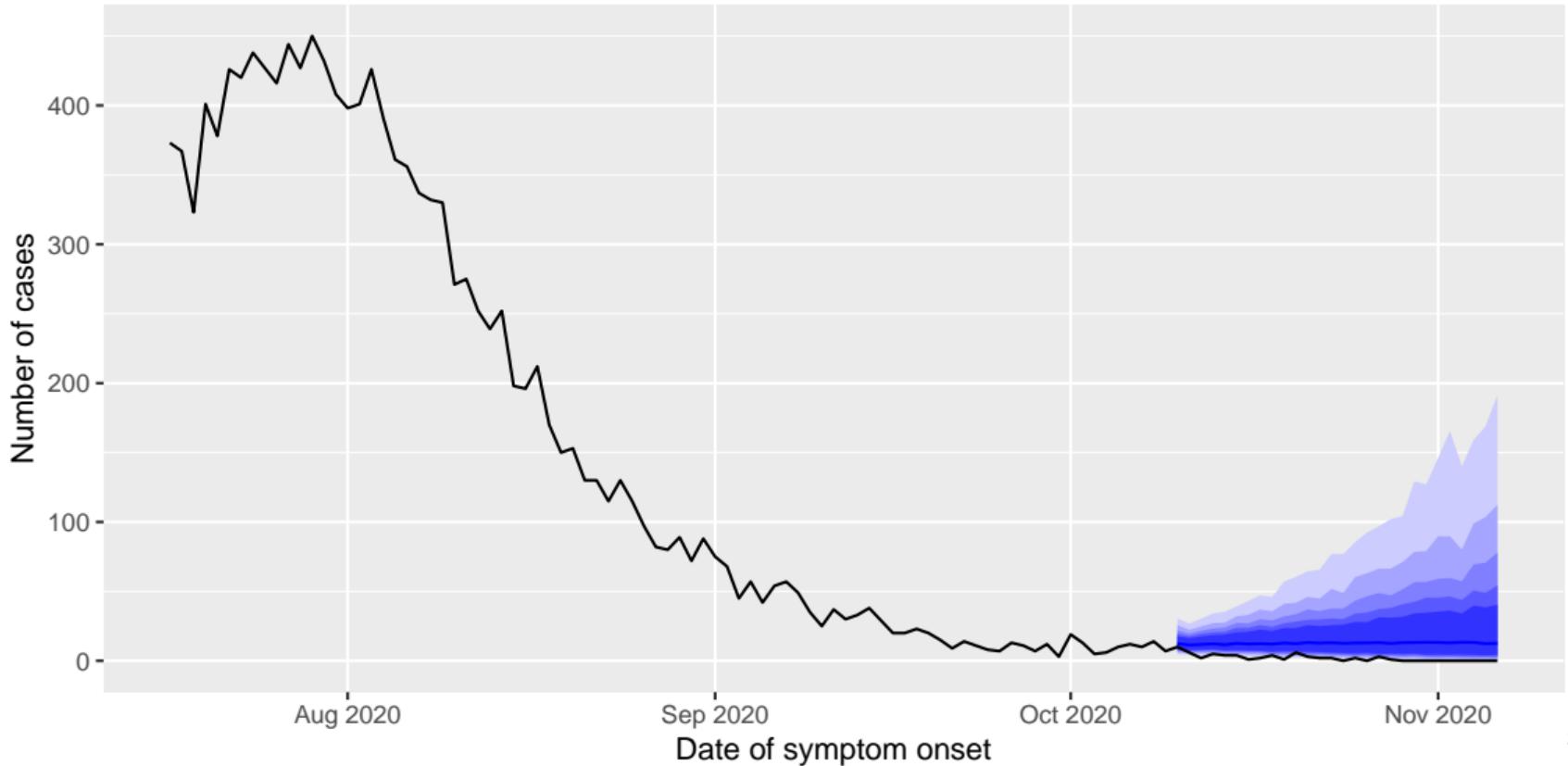
# Ensemble forecasts: Victoria



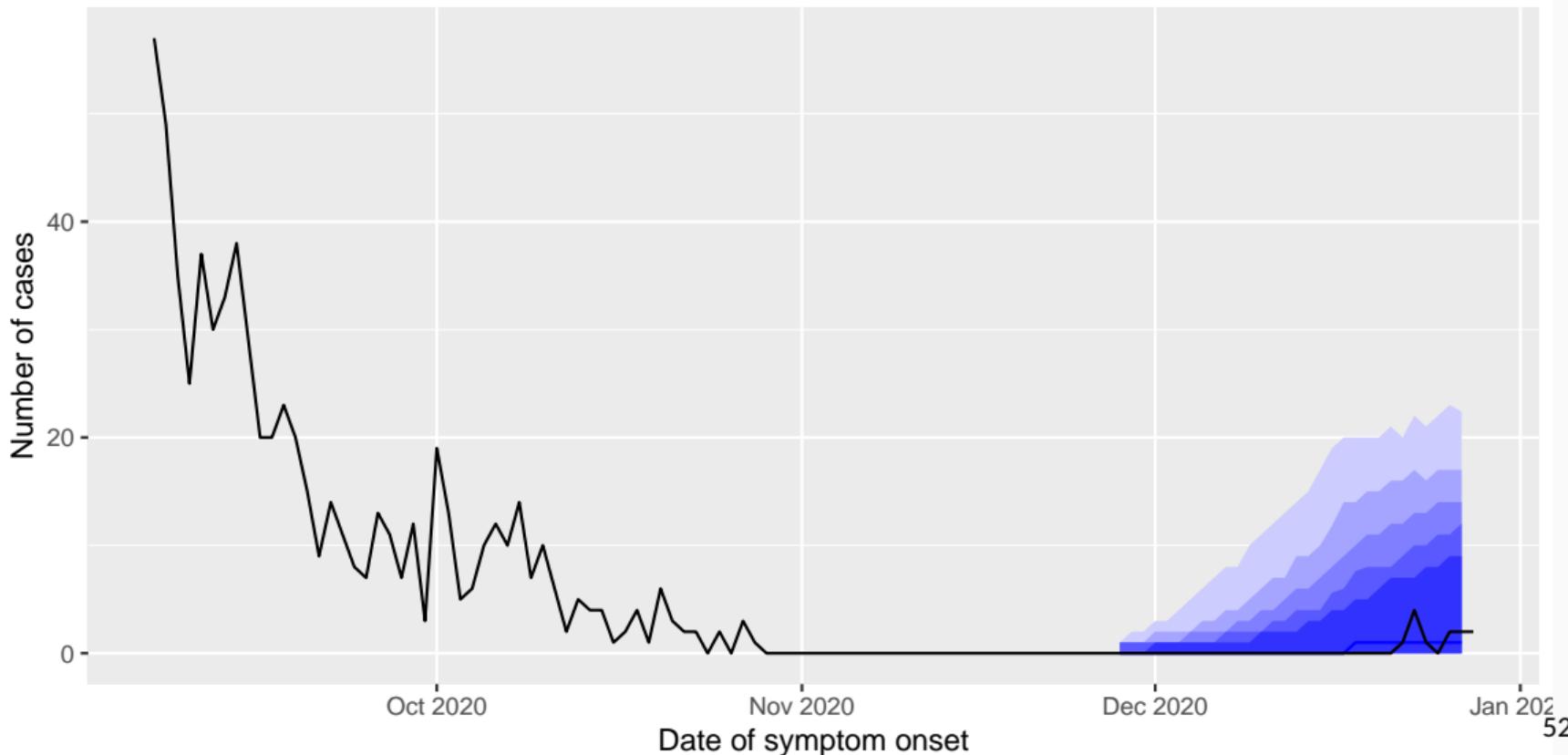
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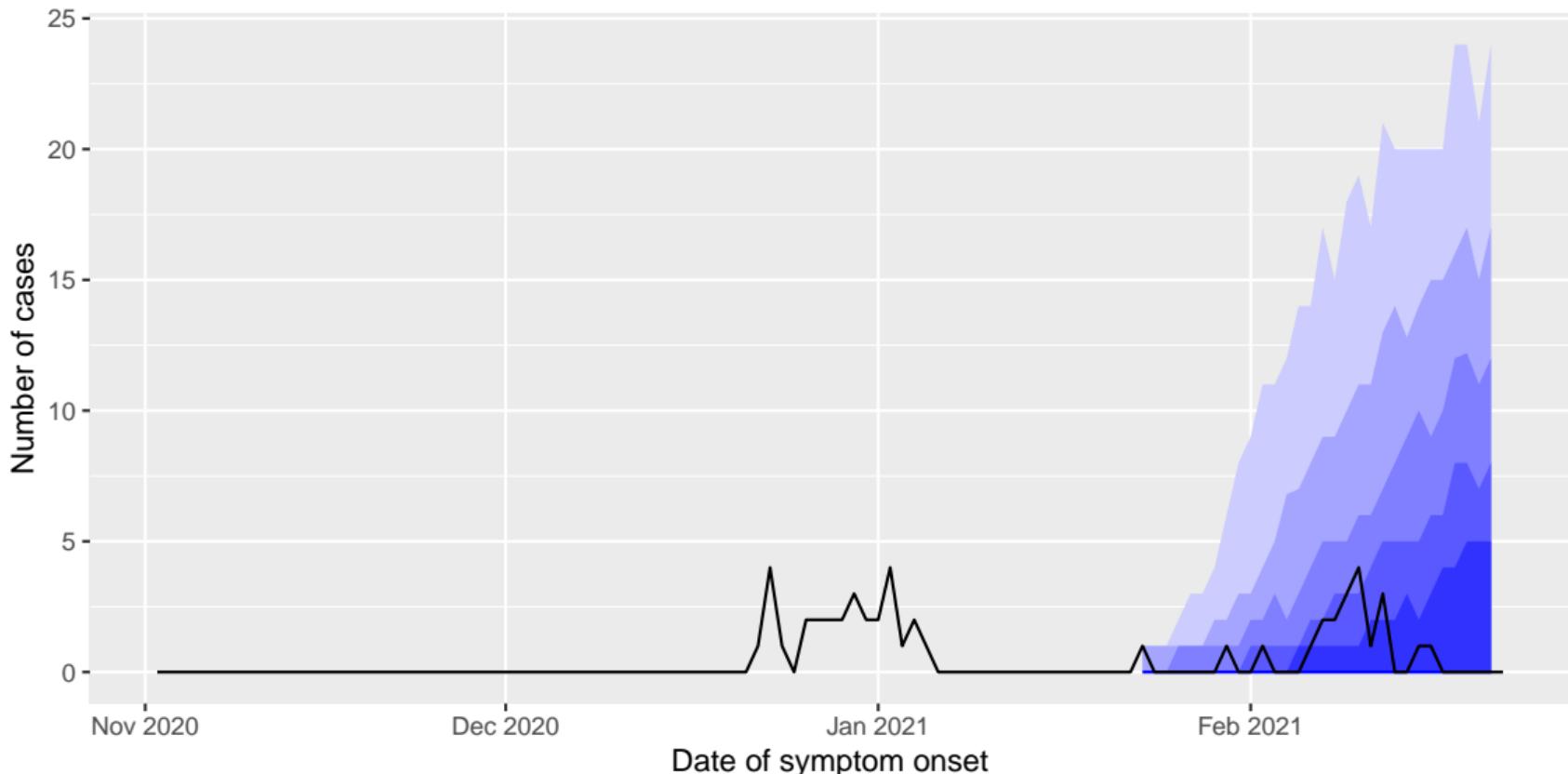
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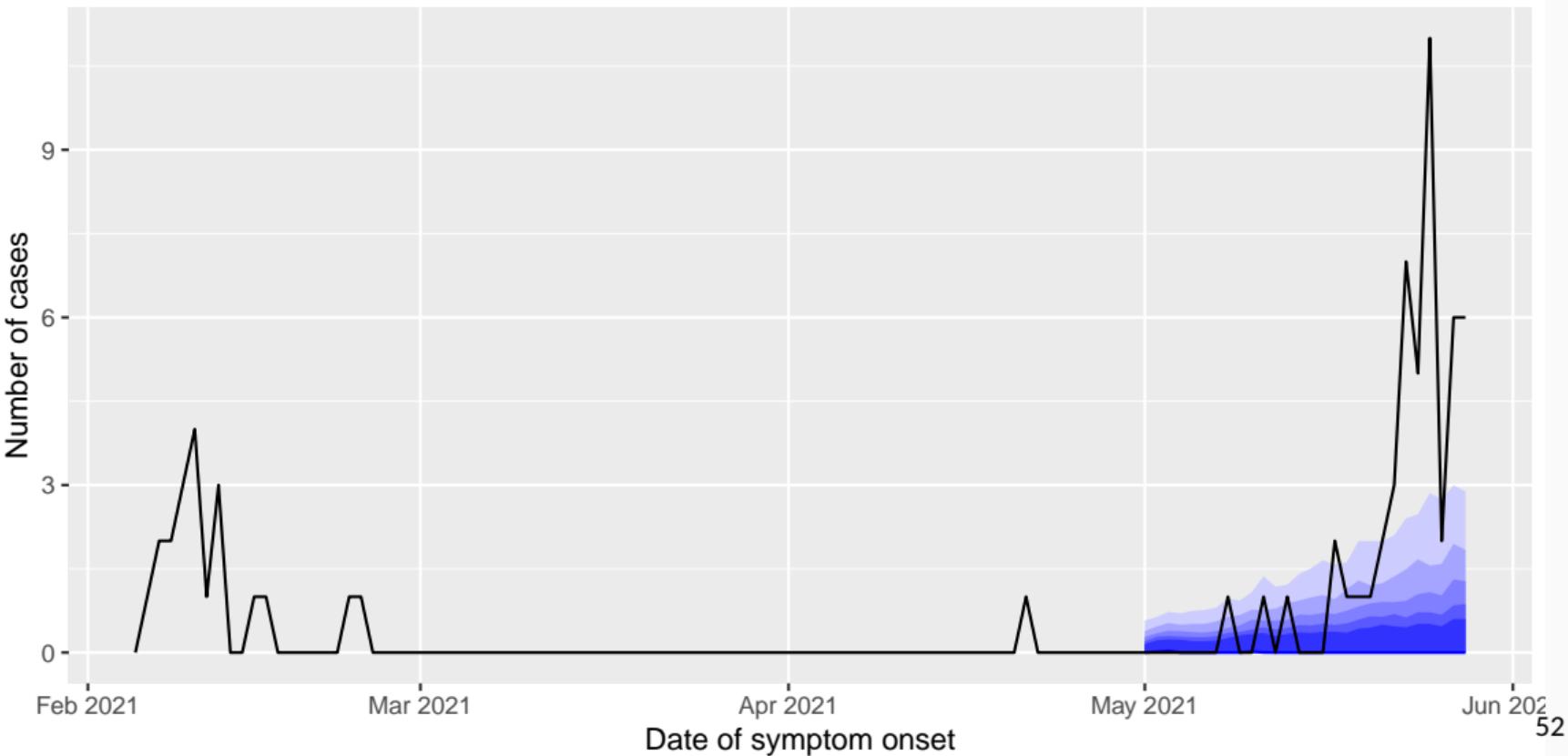
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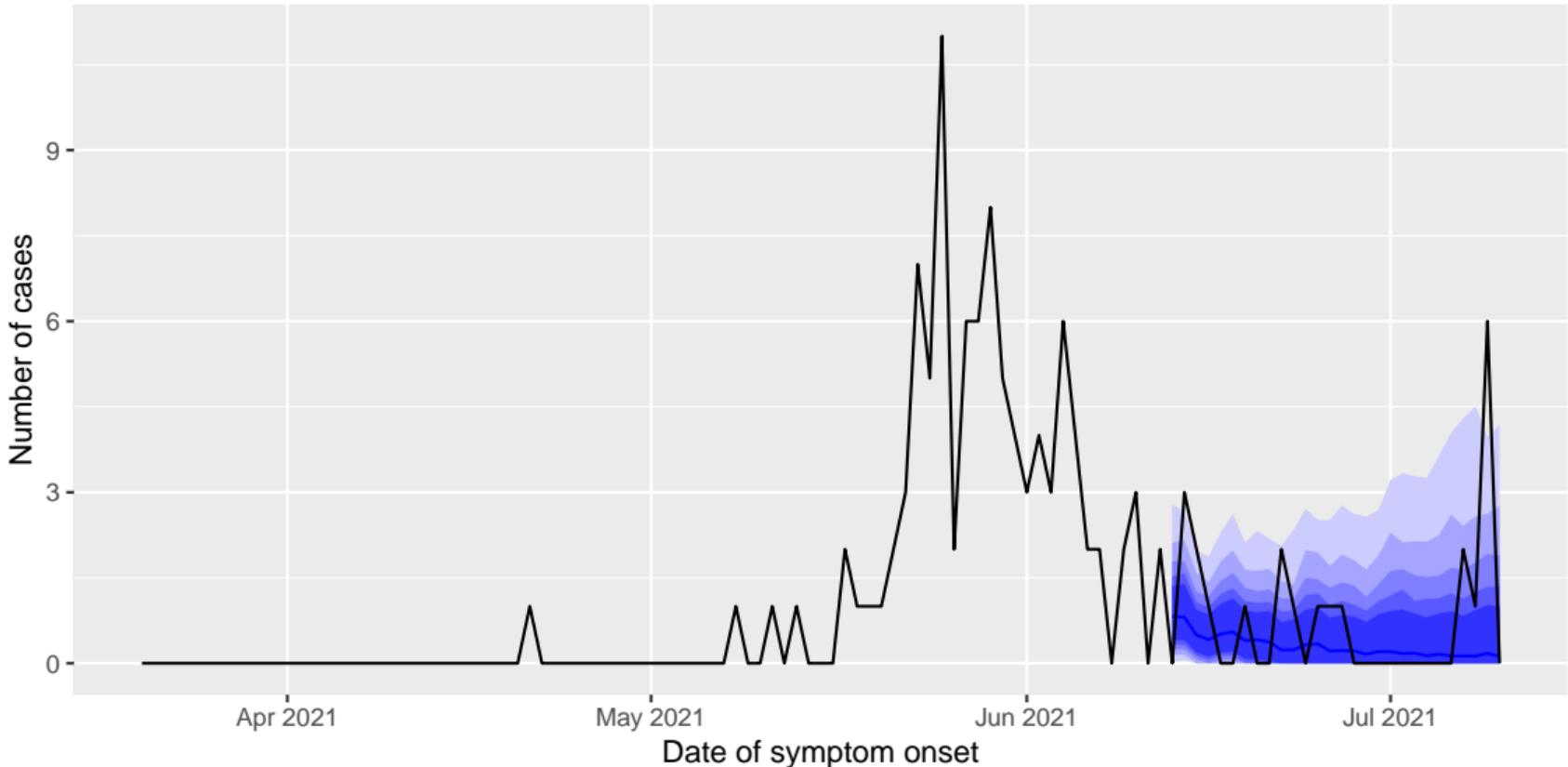
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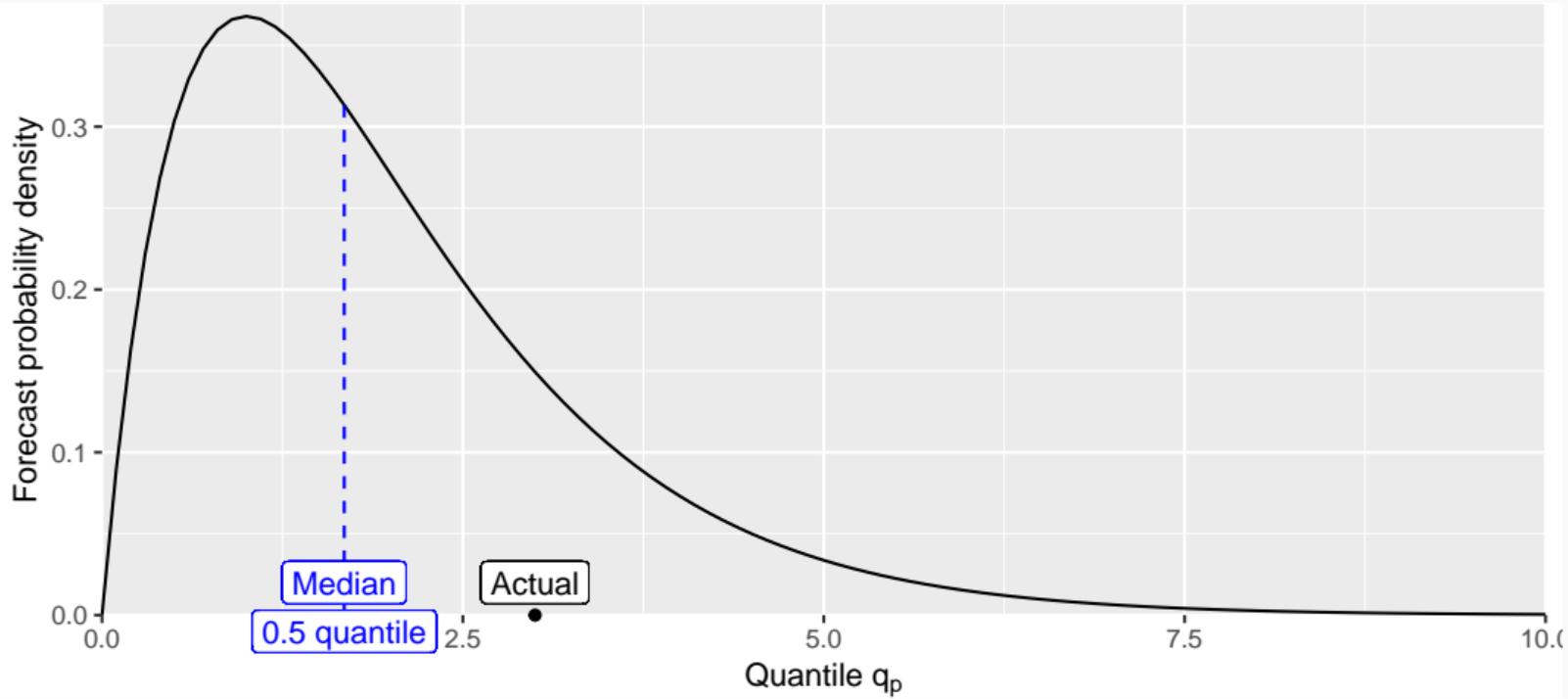
# Forecasting post-pandemic tourism



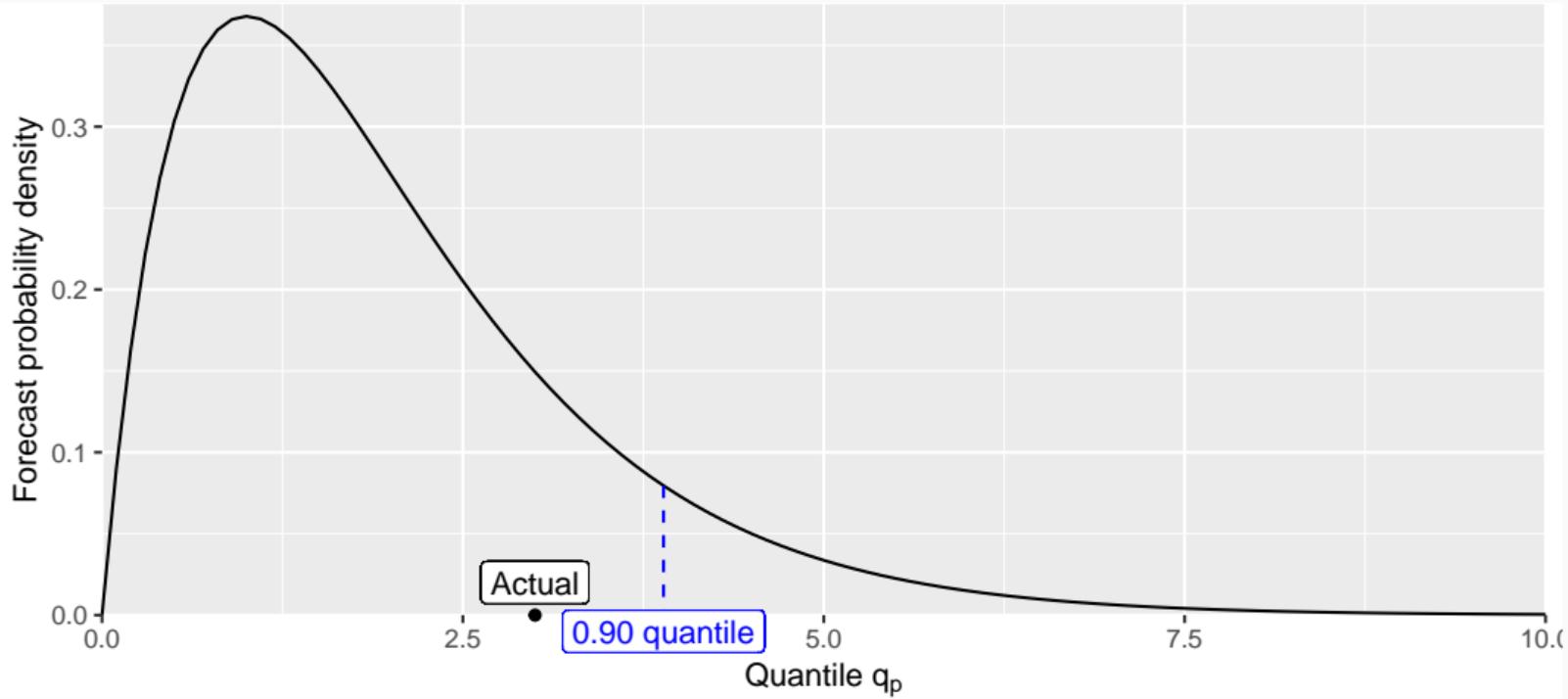
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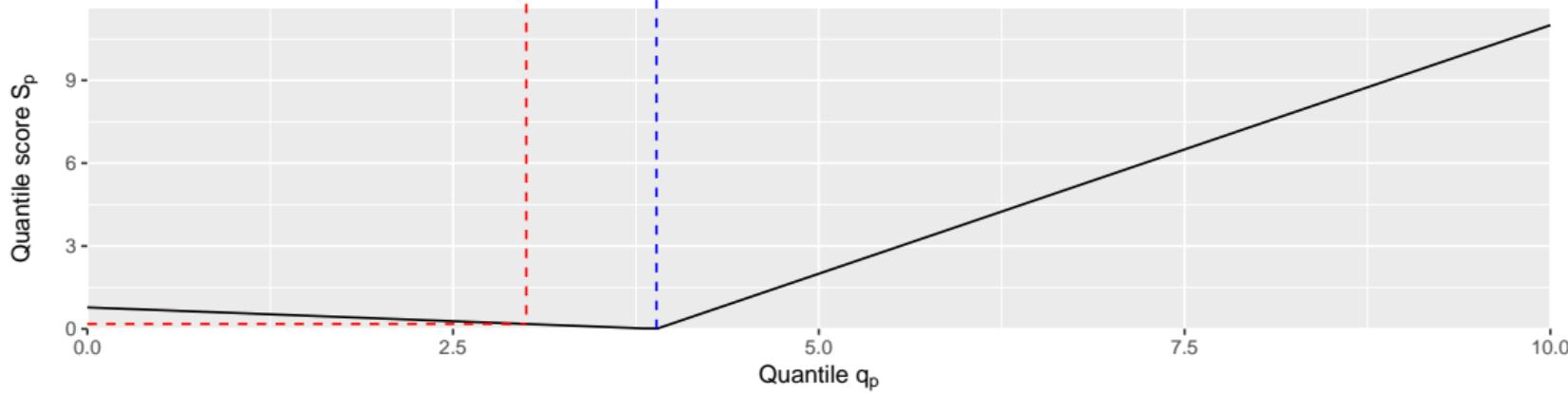
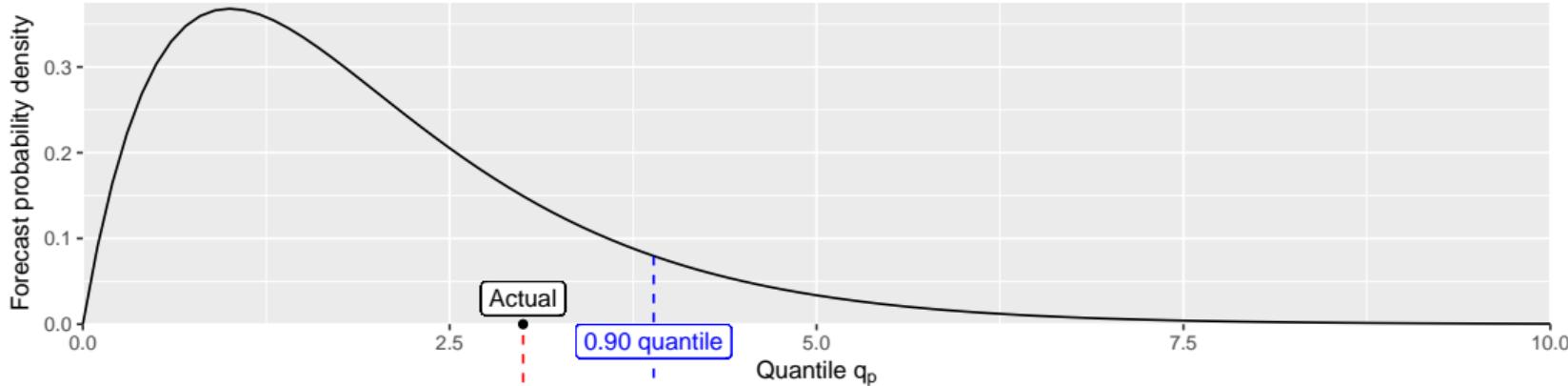
# Evaluating probabilistic forecasts



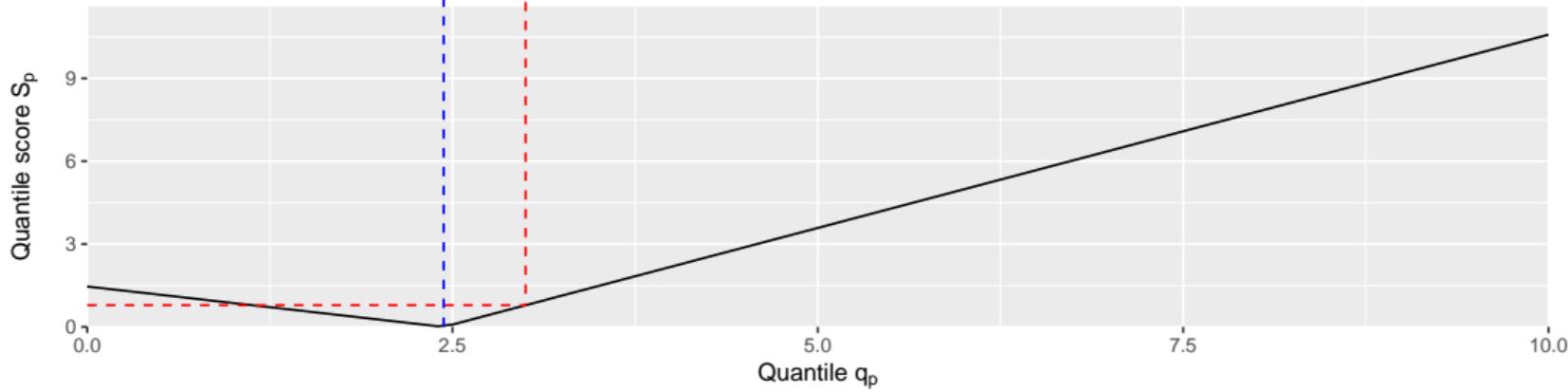
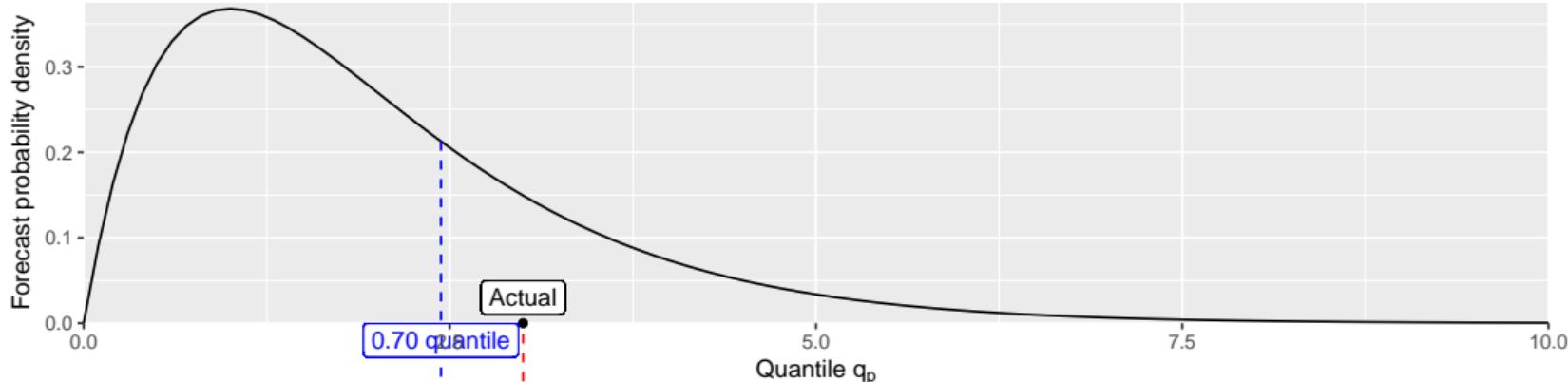
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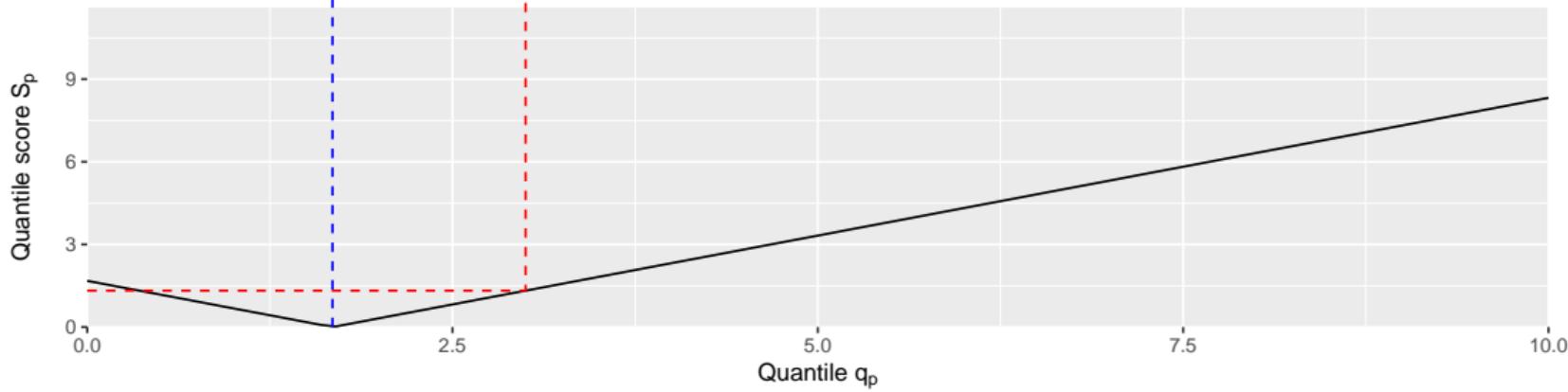
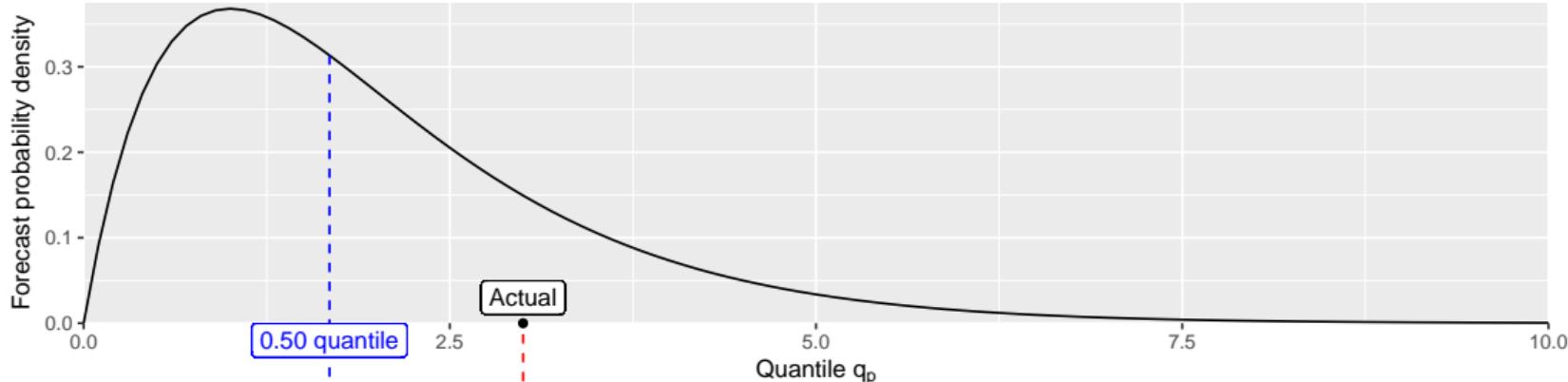
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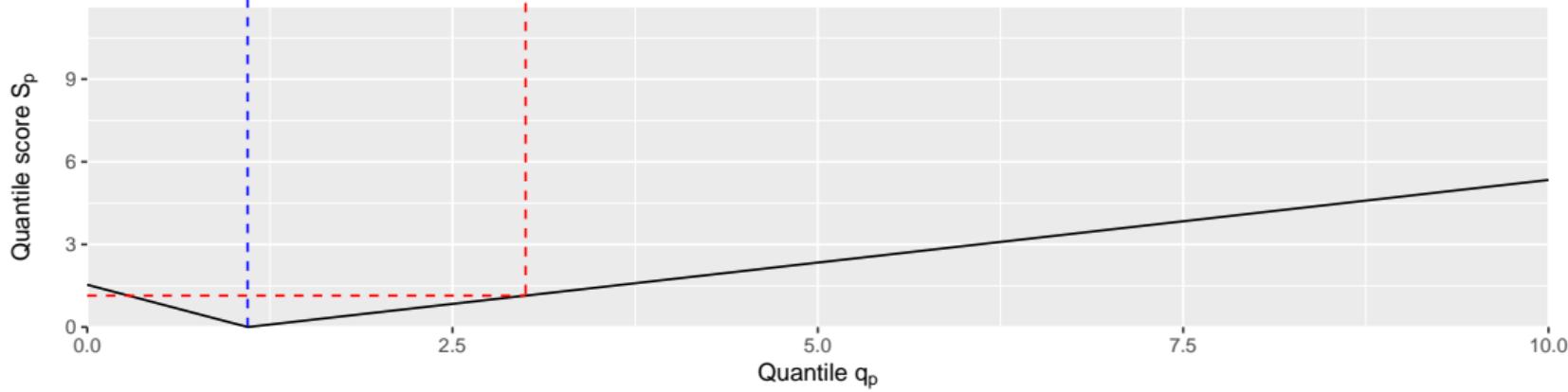
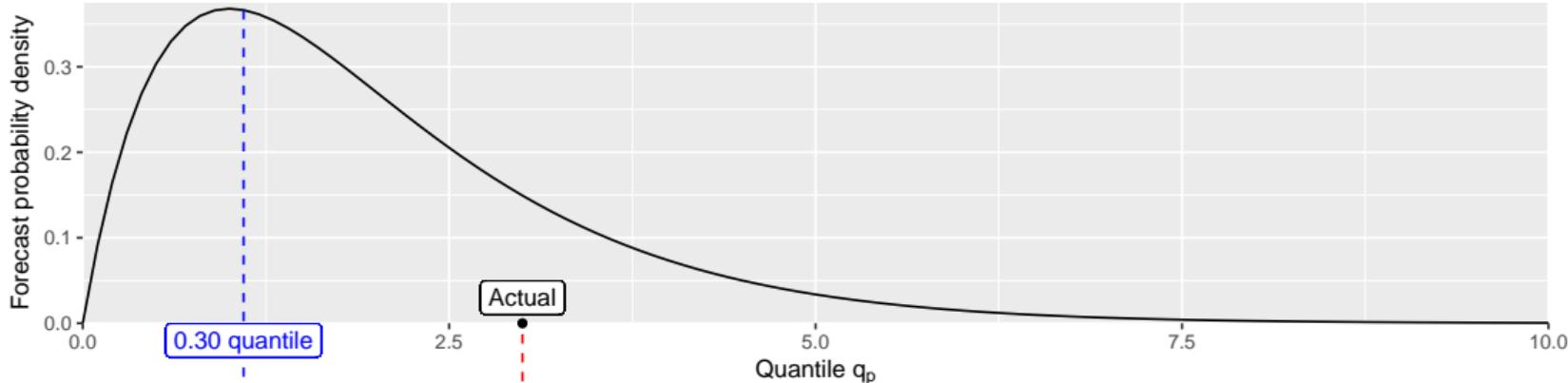
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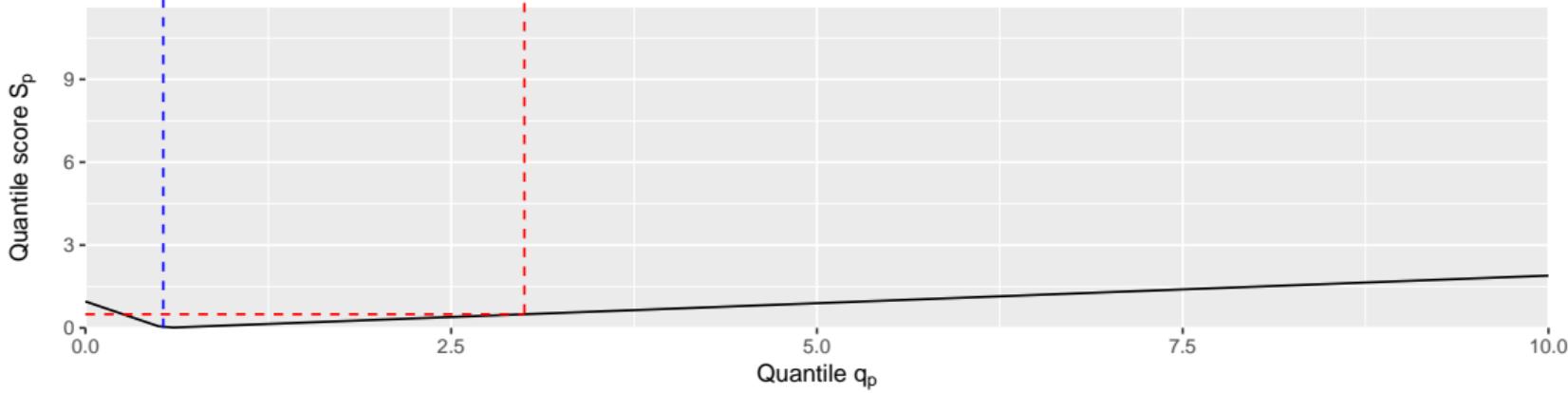
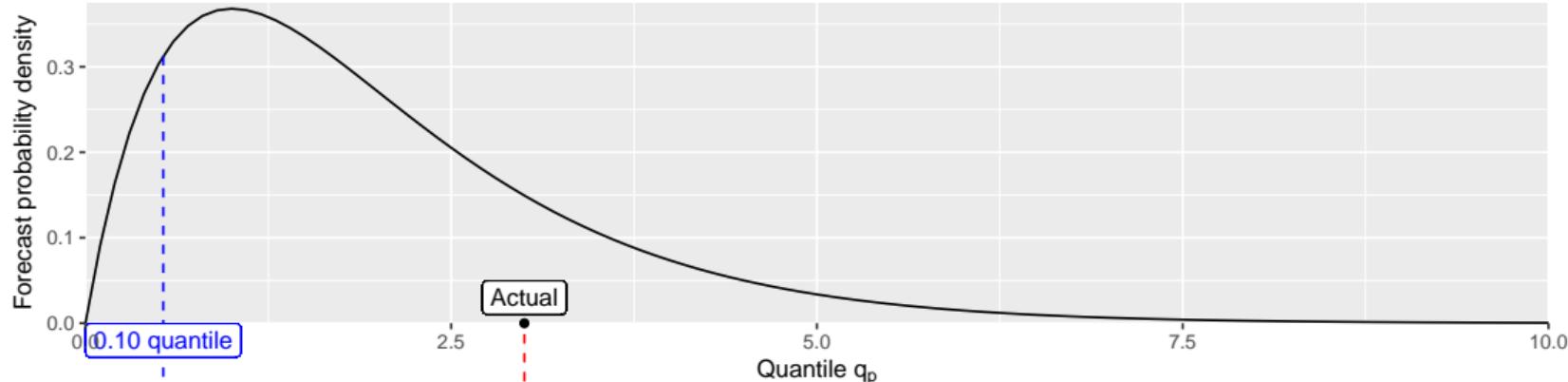
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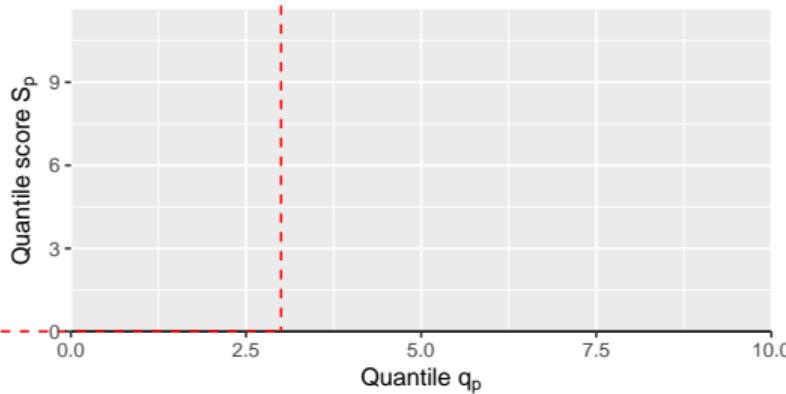
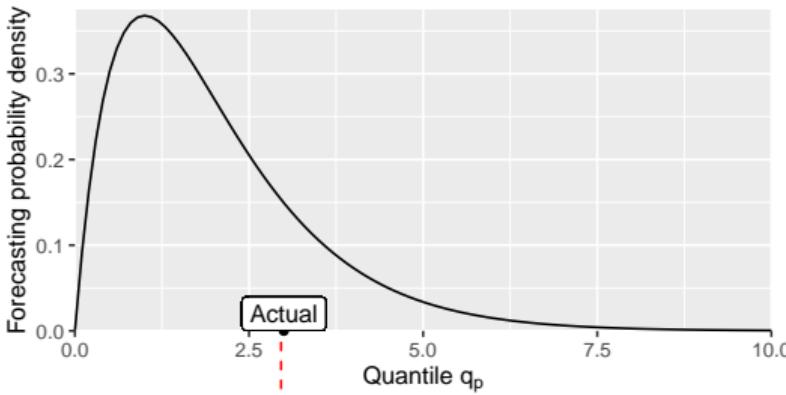
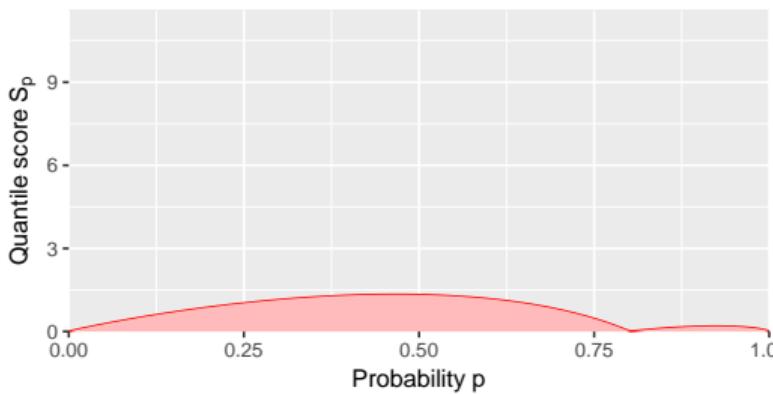


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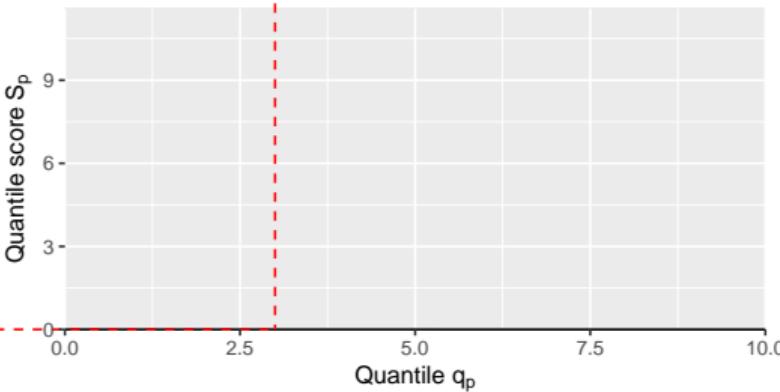
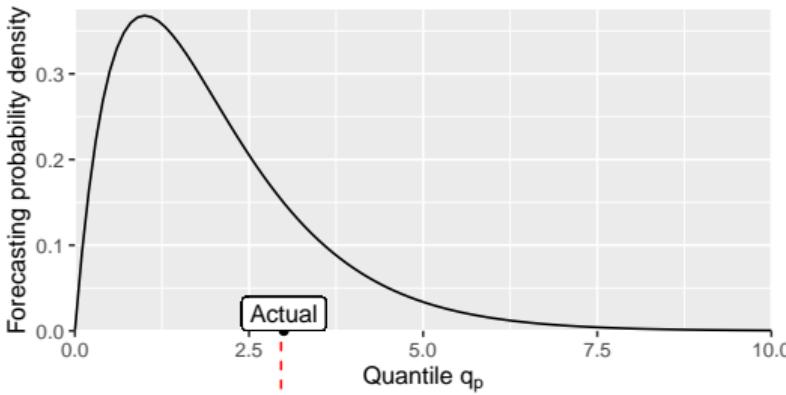
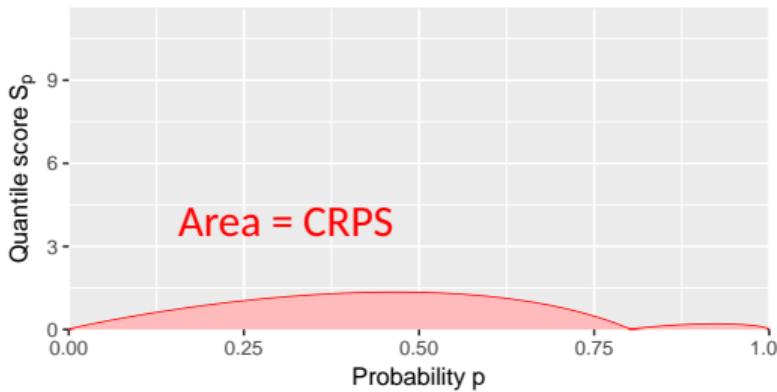


# Evaluating probabilistic forecasts

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# Evaluating probabilistic forecasts

$q_{p,t}$  = quantile forecast with prob.  $p$  at time  $t$ .

$y_t$  = observation at time  $t$

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## Quantile score

$$S_{p,t} = \begin{cases} 2(1-p)|y_t - q_{p,t}|, & \text{if } y_t < q_{p,t} \\ 2p|y_t - q_{p,t}|, & \text{if } y_t \geq q_{p,t} \end{cases}$$

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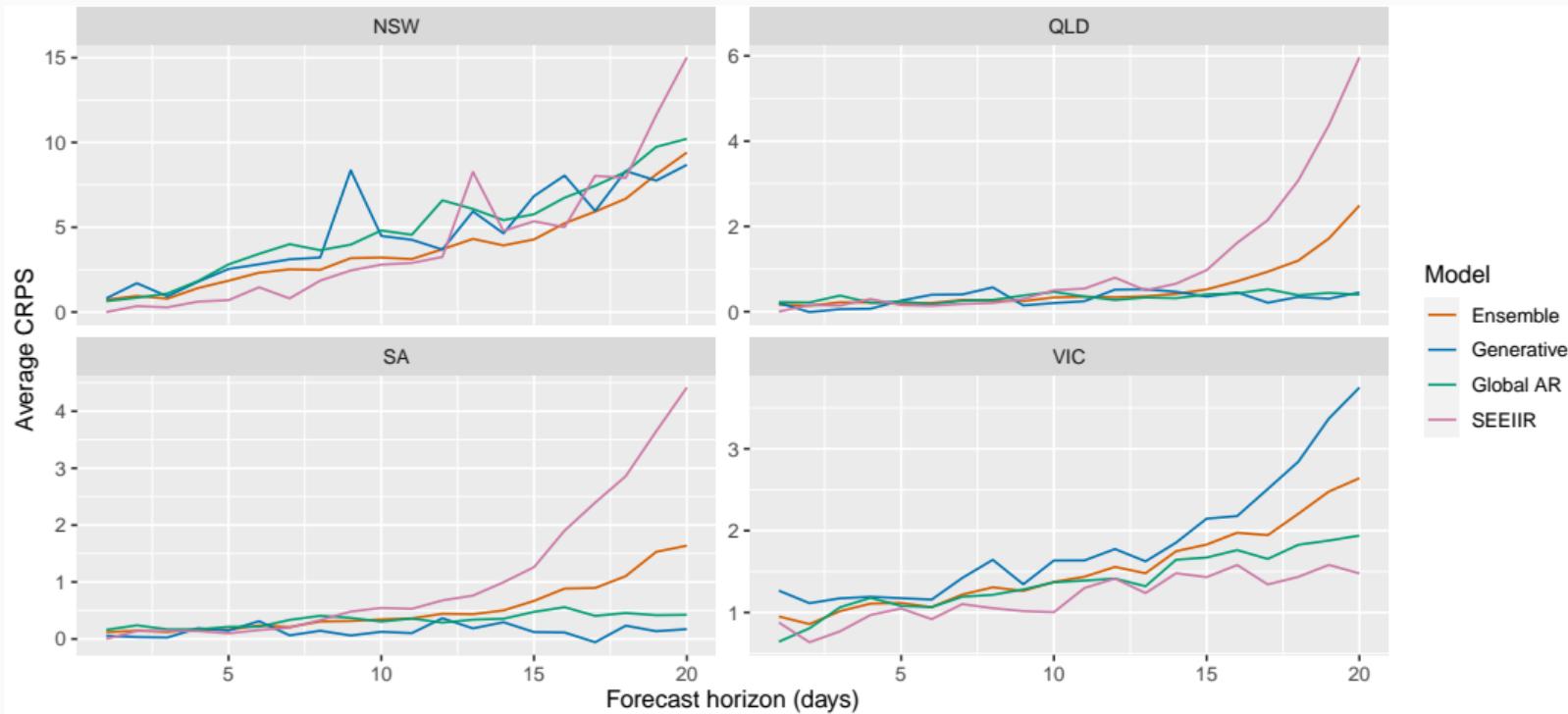
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- Low  $S_{p,t}$  is good
- Multiplier of 2 often omitted, but useful for interpretation
- $S_{p,t}$  like absolute error (weighted to account for likely exceedance)
- Average  $S_{p,t}$  over  $p$  = CRPS (Continuous Ranked Probability Score)

# CRPS: Continuous Ranked Probability Score



For weekly forecasts created from 17 September 2020 to 15 June 2021

# When should we give up?

- When there is insufficient data?
- When the models give implausible forecasts?
- When the forecast uncertainty is too large to assist decision making?

## More information

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 [@robjhyndman](https://twitter.com/robjhyndman)

 [@robjhyndman](https://github.com/robjhyndman)

 [rob.hyndman@monash.edu](mailto:rob.hyndman@monash.edu)