



QUANTIFYING RISK, ENABLING OPPORTUNITY

Measuring in-hospital claims volatility

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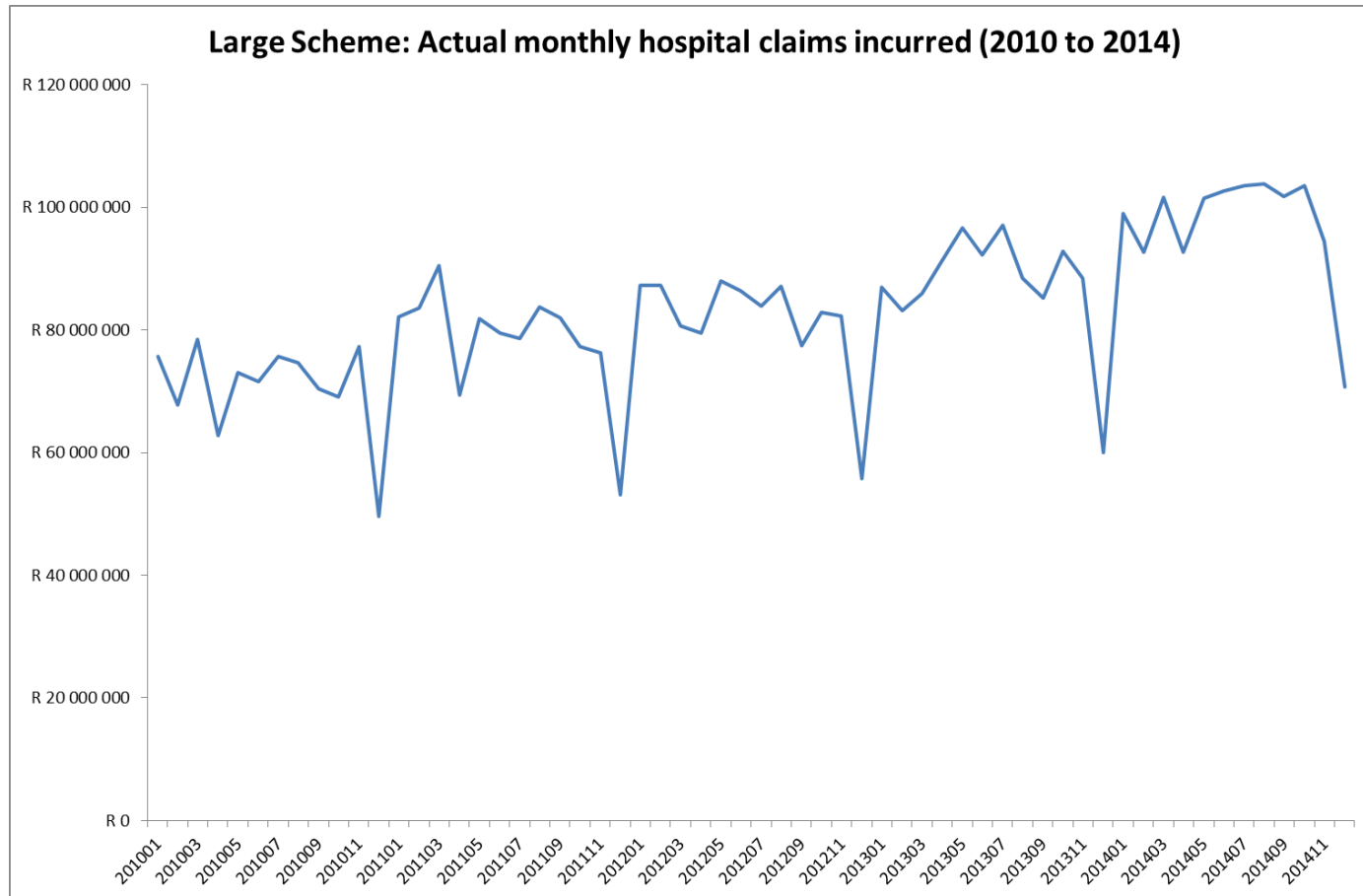
7 May 2015

TOWERS WATSON 

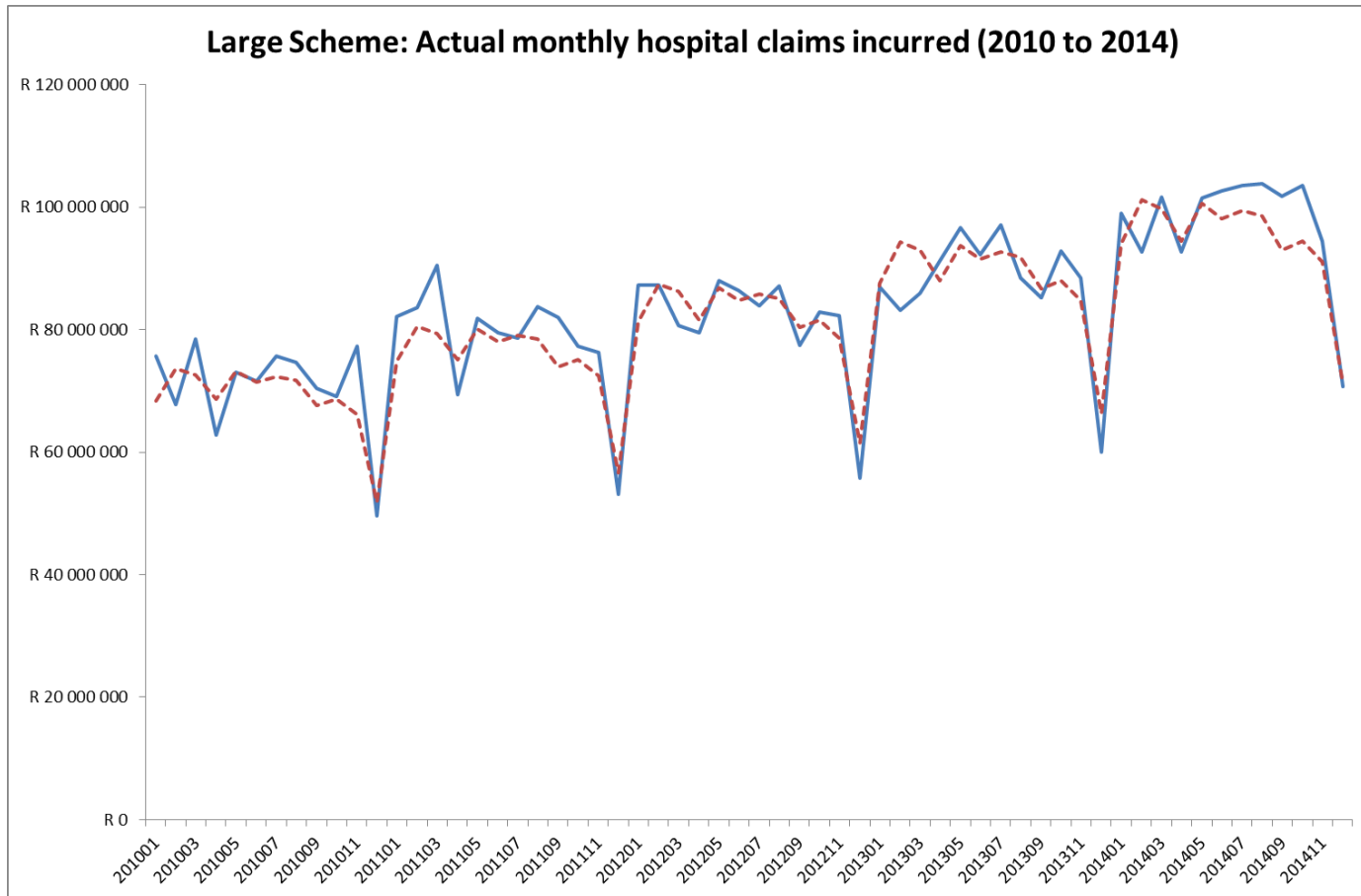
Agenda

- ❖ Inspiration for the research
- ❖ Research to date:
 - ❖ Calculating claim residuals
 - ❖ Impact of size of risk pool
 - ❖ Distribution of residuals
 - ❖ Evidence of auto-regression
 - ❖ Simulations
- ❖ Lessons so far

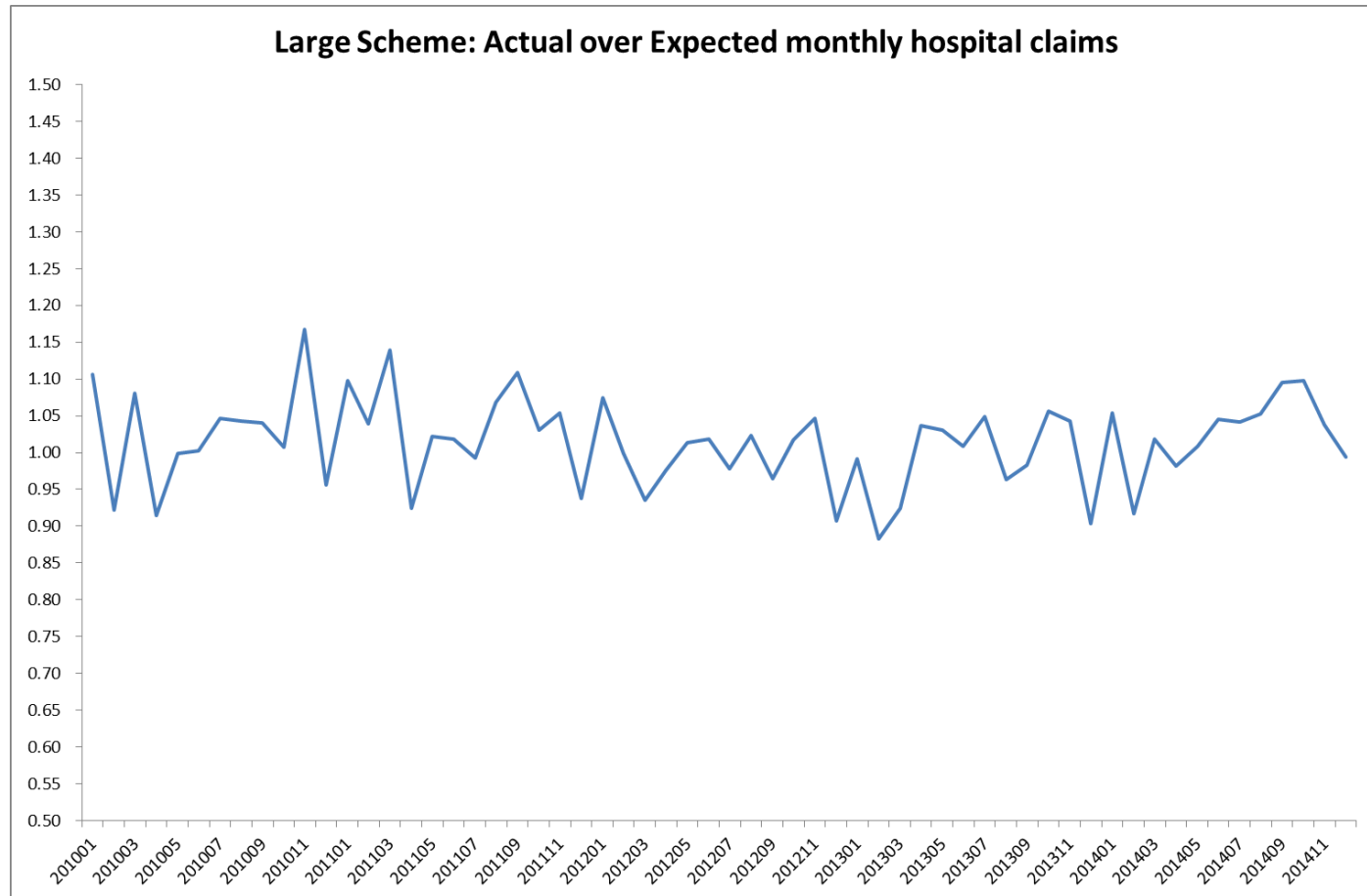
Actual monthly hospital claims incurred values



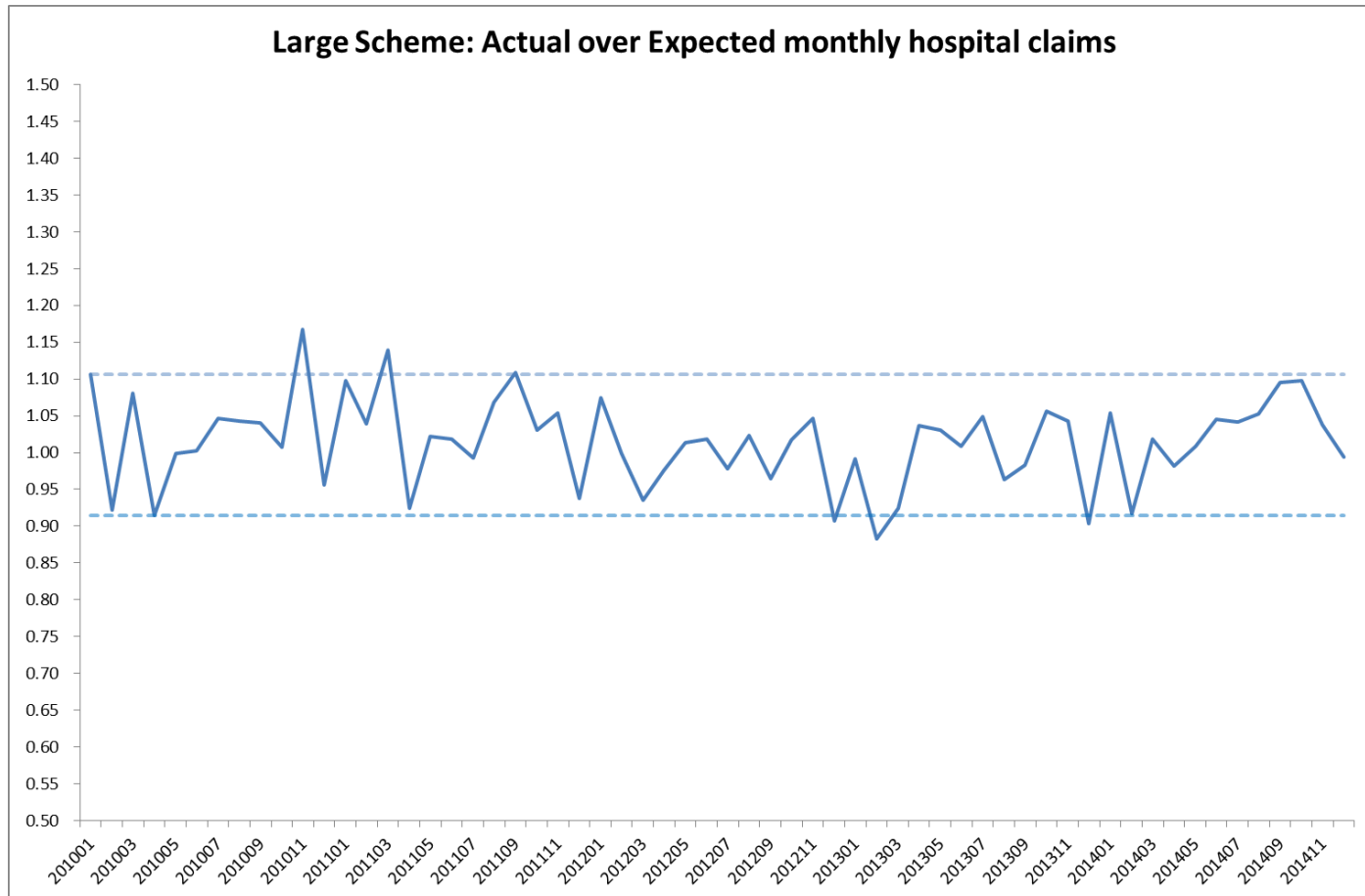
Fit claims forecast model to data points



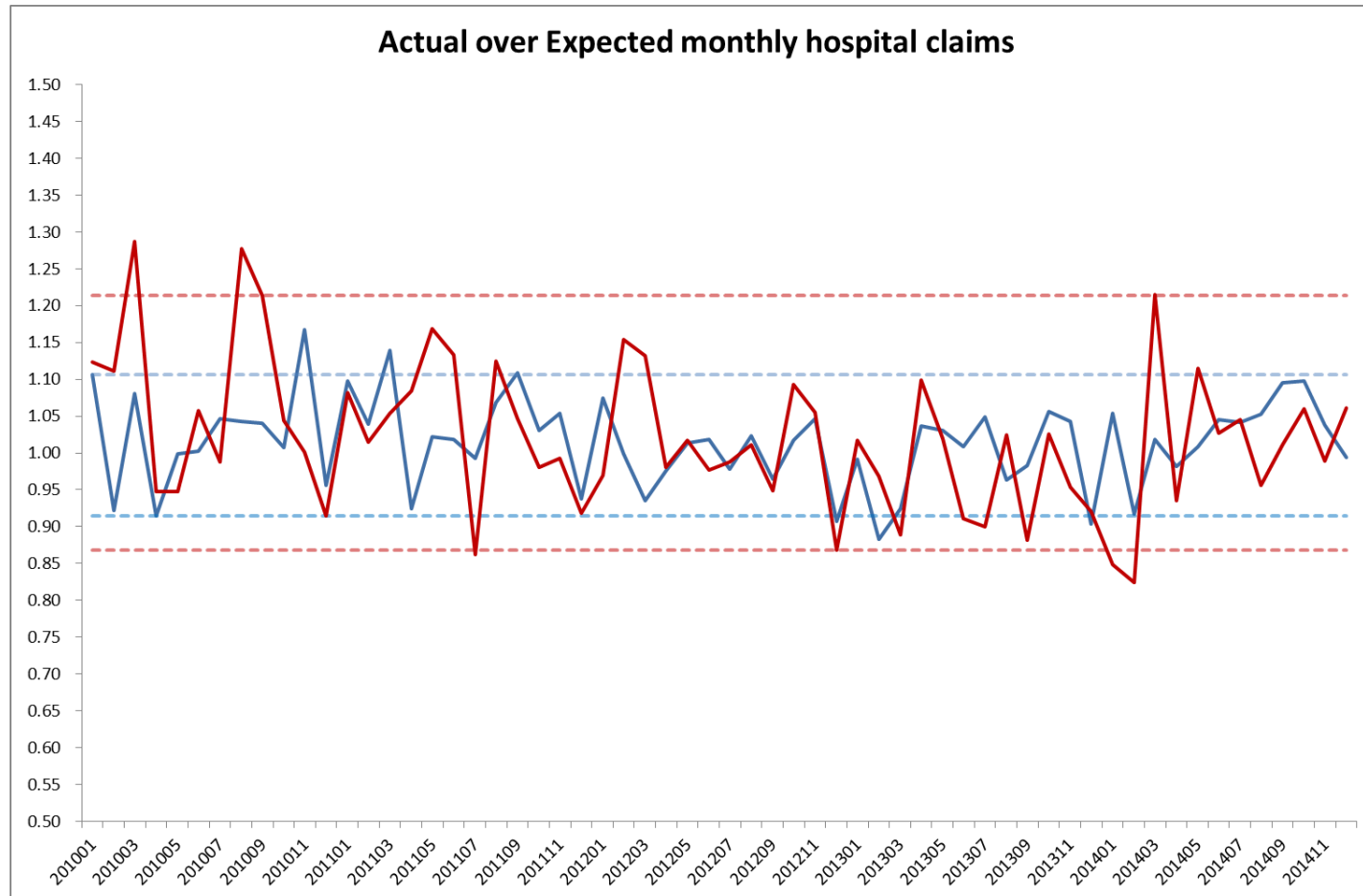
Claim residuals plotted from 2010 to 2014



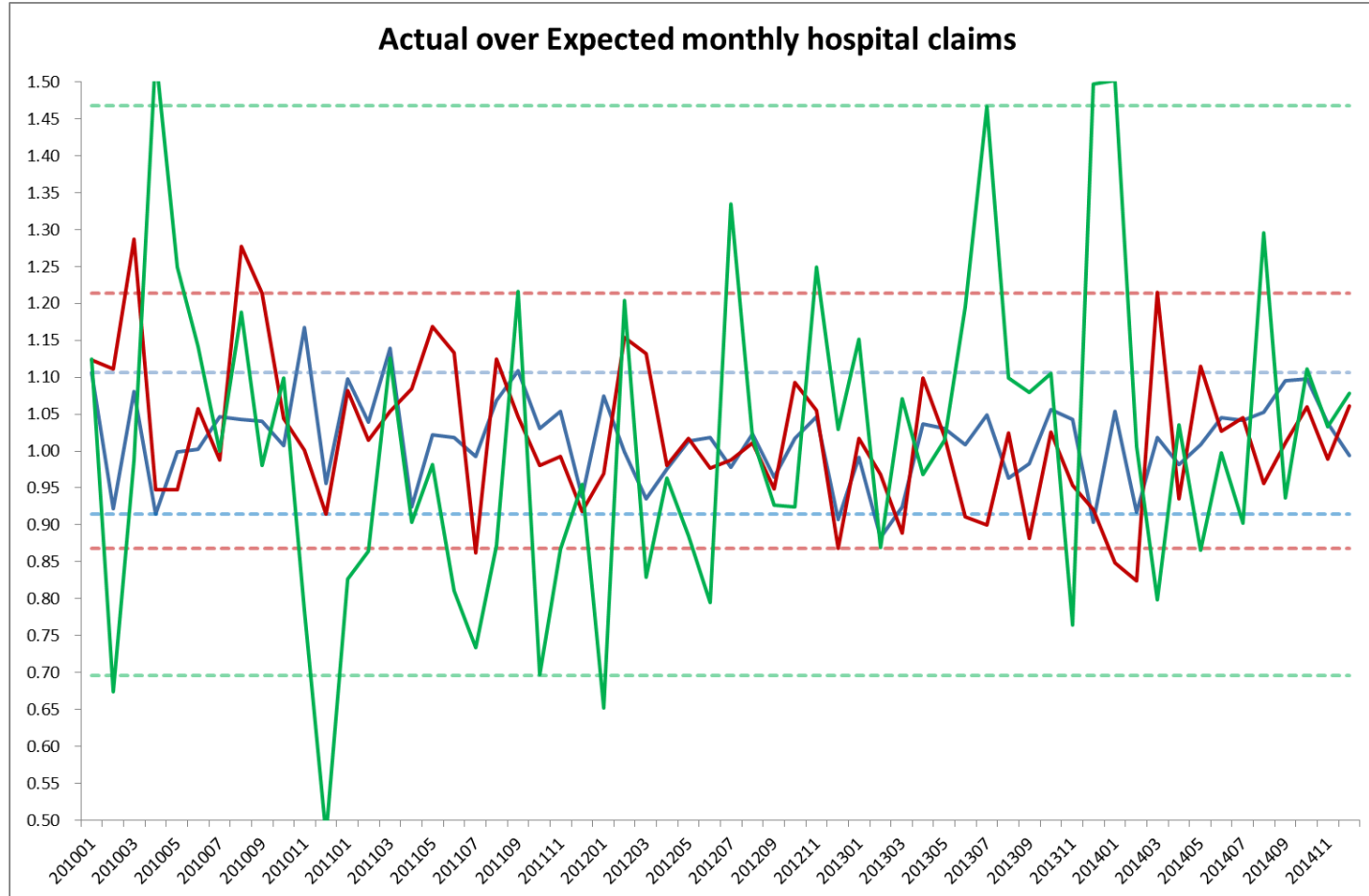
Add 5th to 95th percentile range to residuals



Large Scheme and Medium Scheme residuals



Large Scheme, Medium and Small Scheme residuals



Analysis of residuals

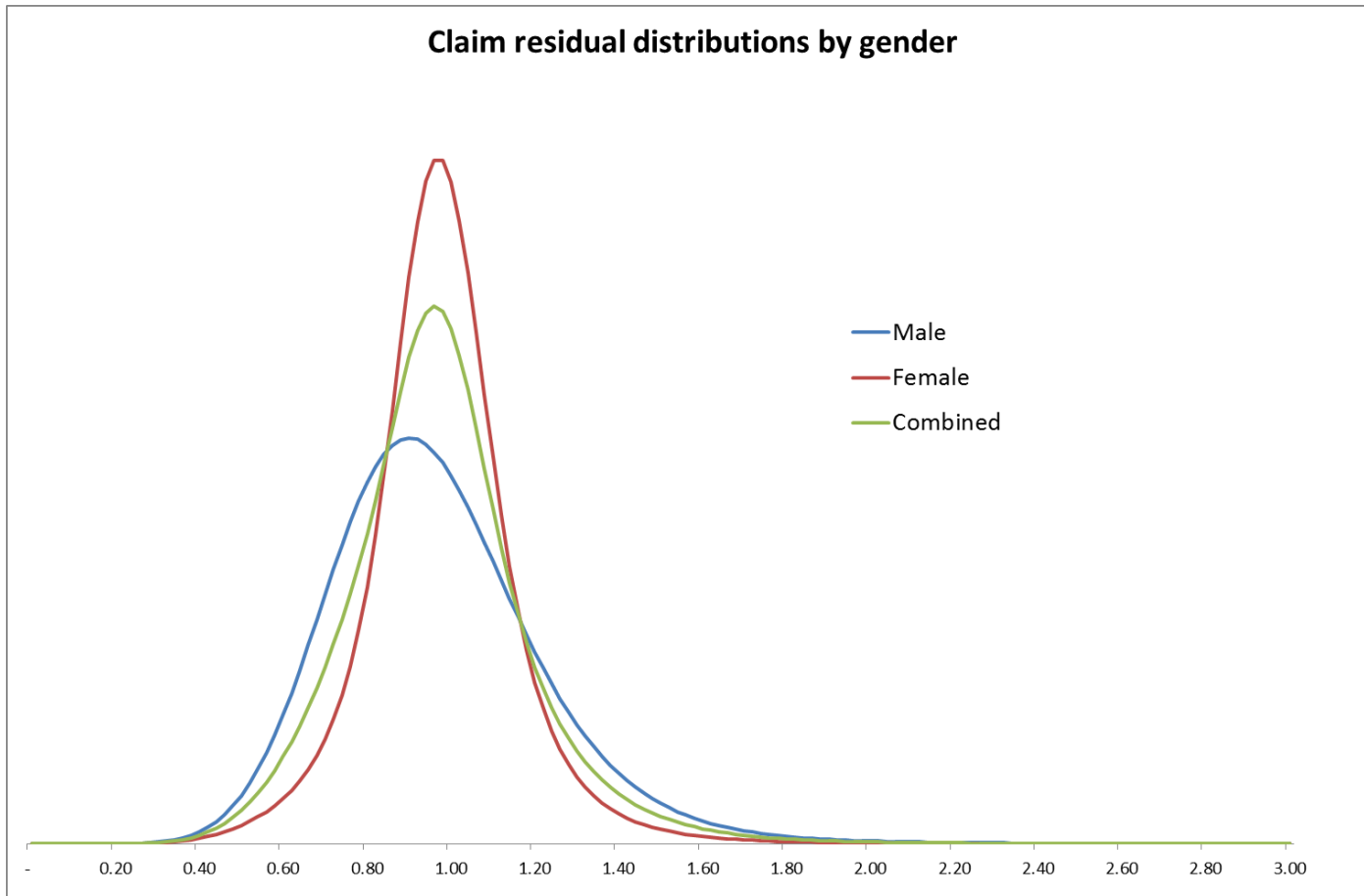
❖ 95th percentiles for different risk pools:

- ❖ Large scheme 1.11x mean
- ❖ Medium scheme 1.21x mean
- ❖ Small scheme 1.47x mean

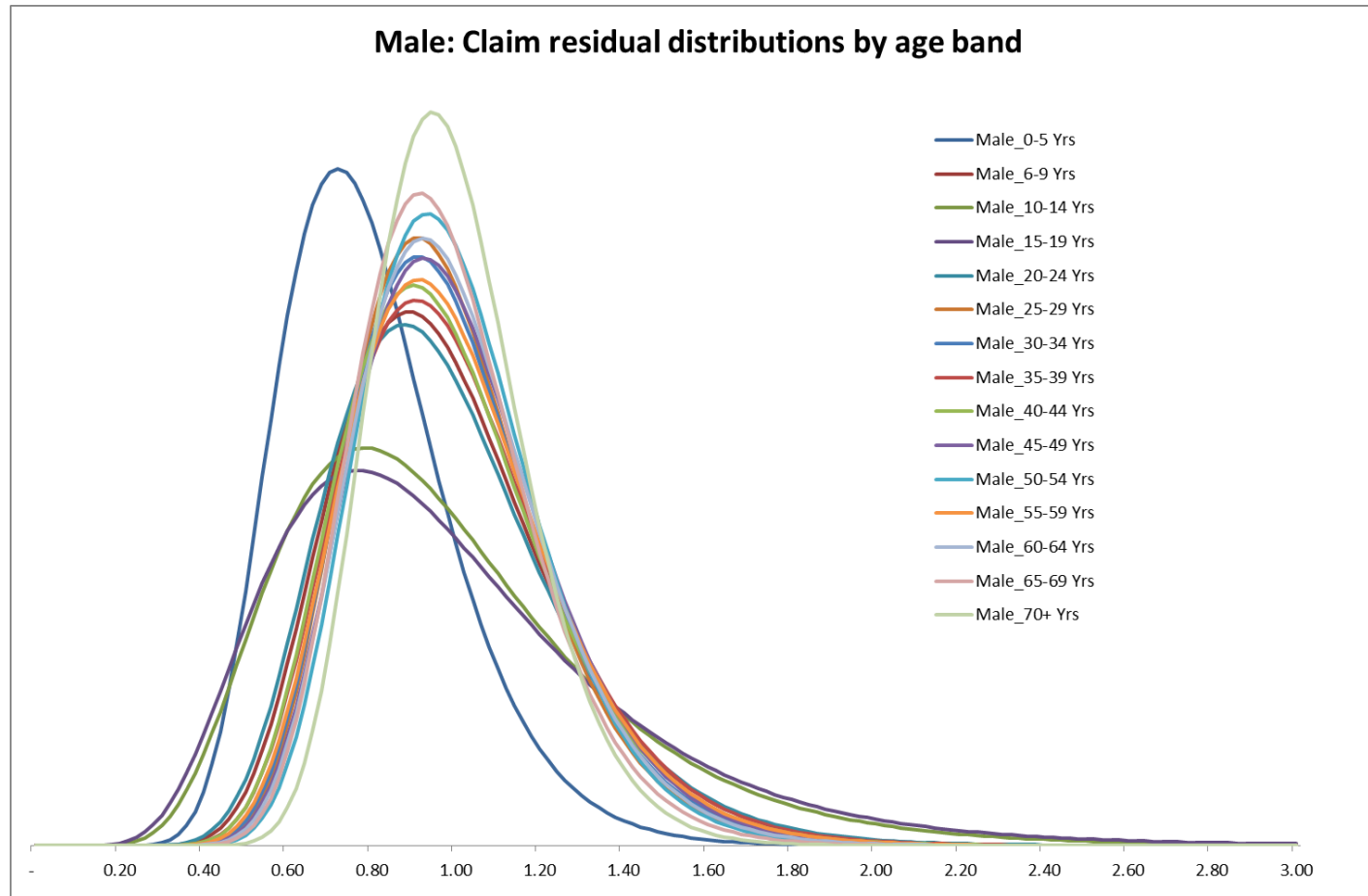
❖ Impact of risk-pool make-up:

- ❖ Number of members
- ❖ Hospital utilisation
- ❖ Age and gender make-up

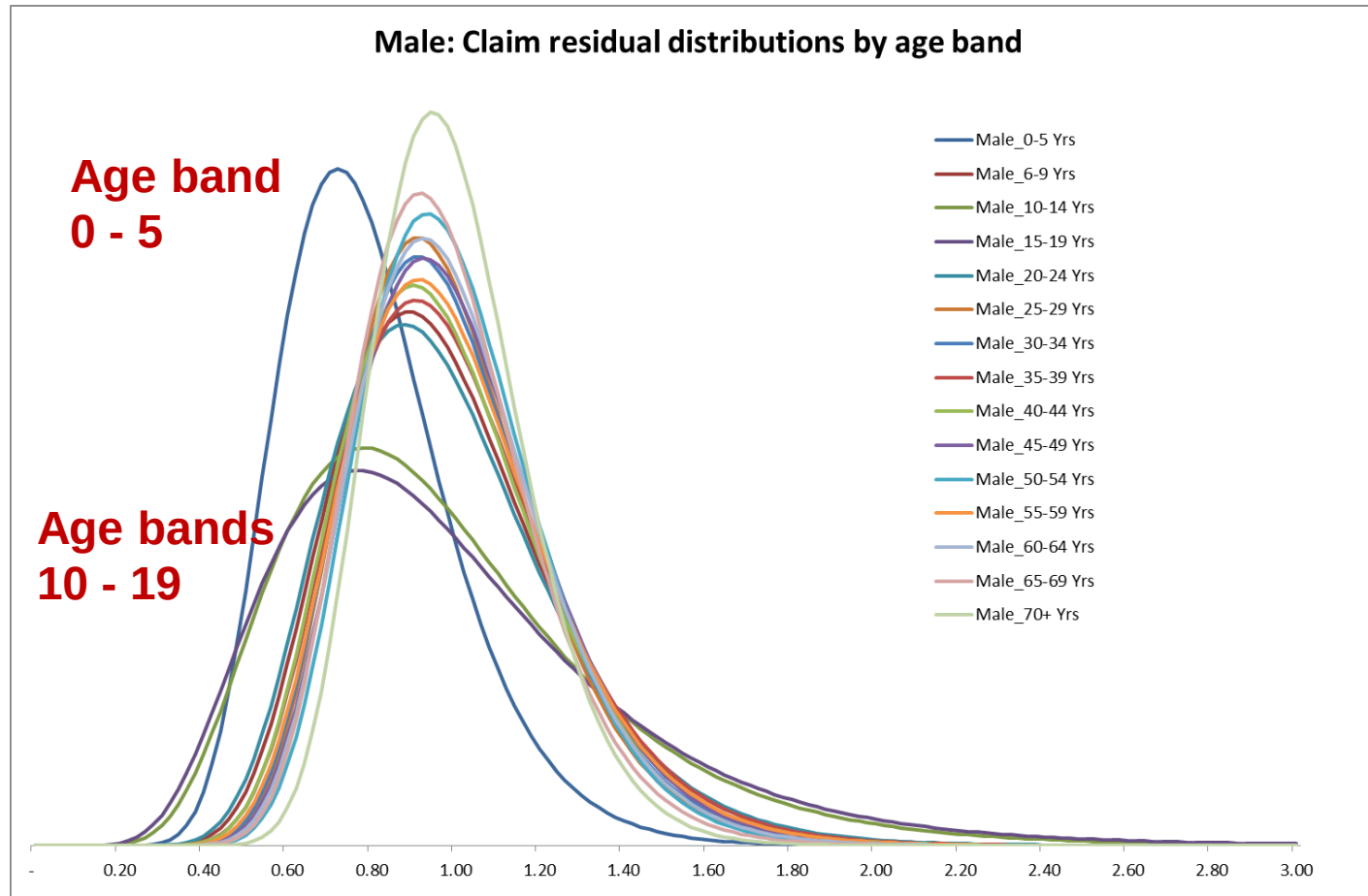
Distribution of residuals by gender



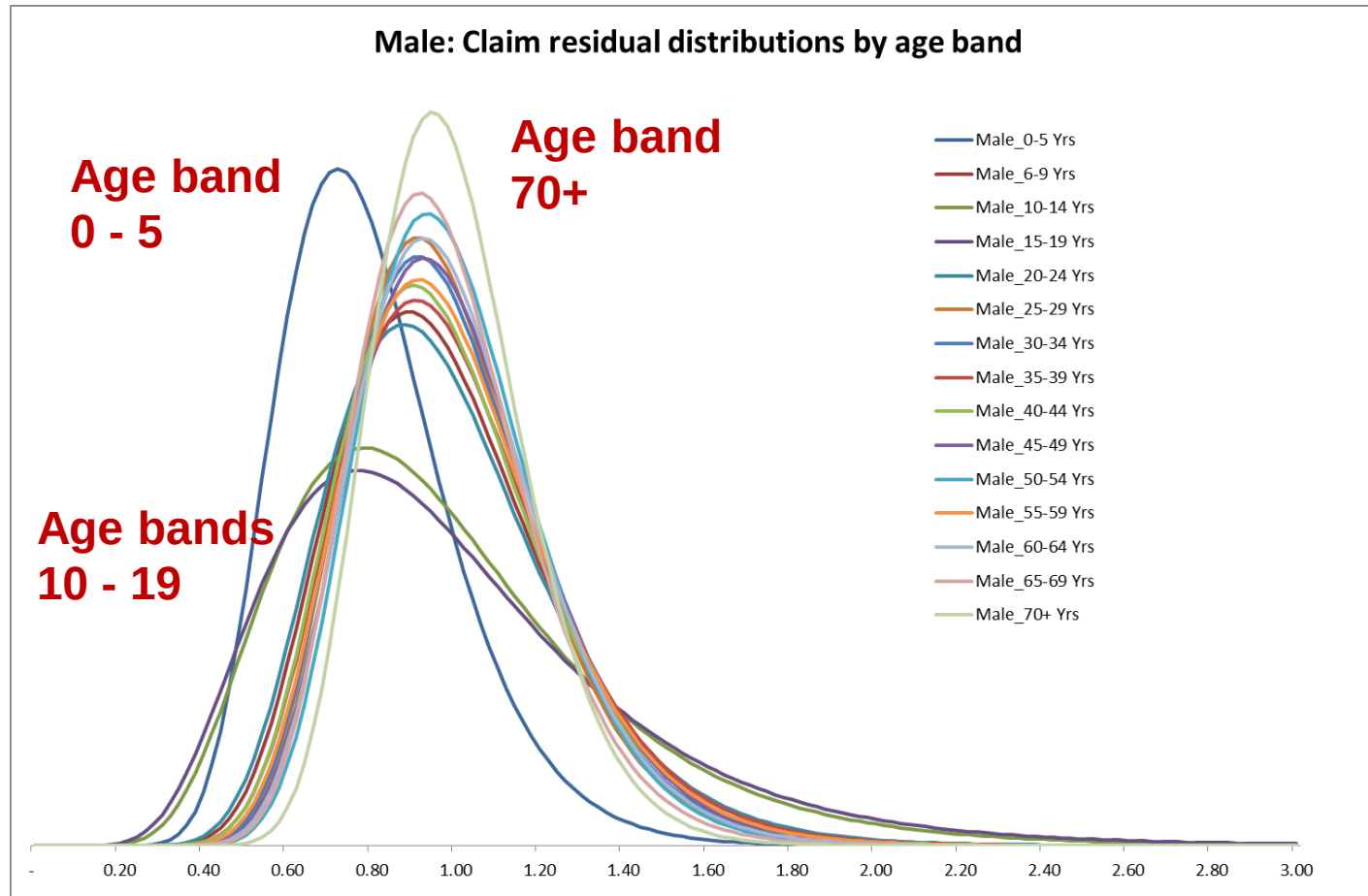
Distribution of residuals by gender and age band



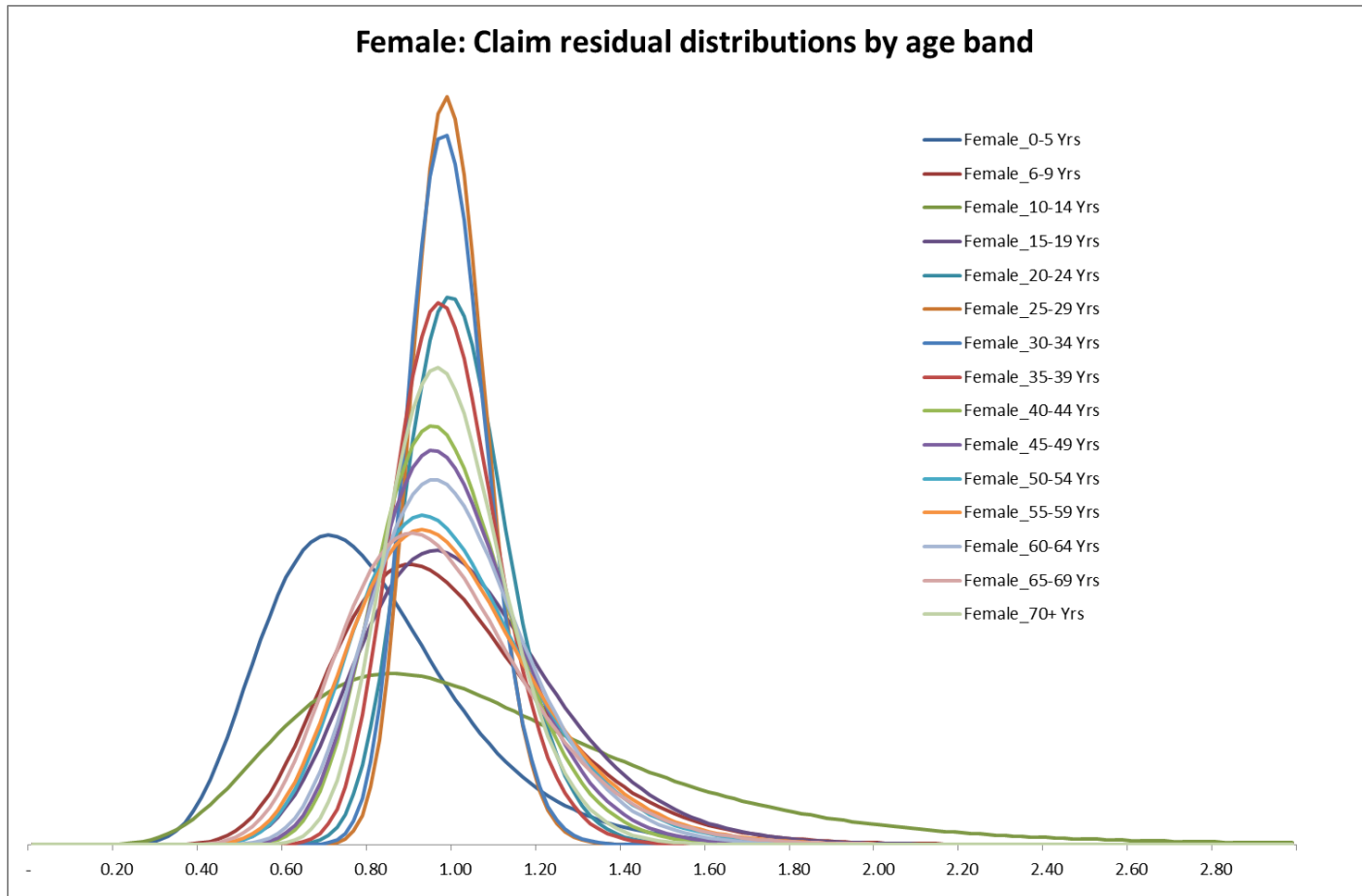
Distribution of residuals by gender and age band



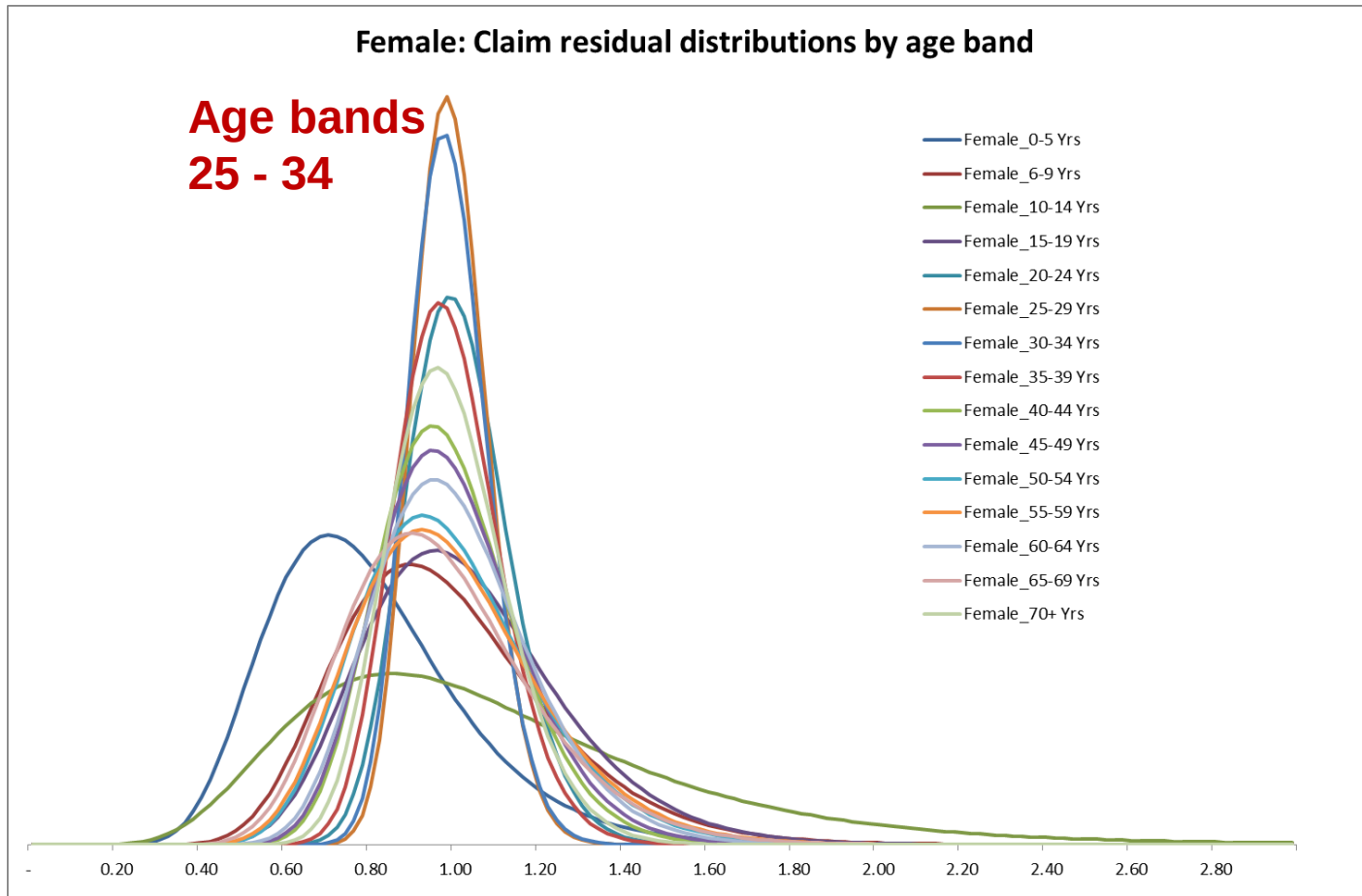
Distribution of residuals by gender and age band



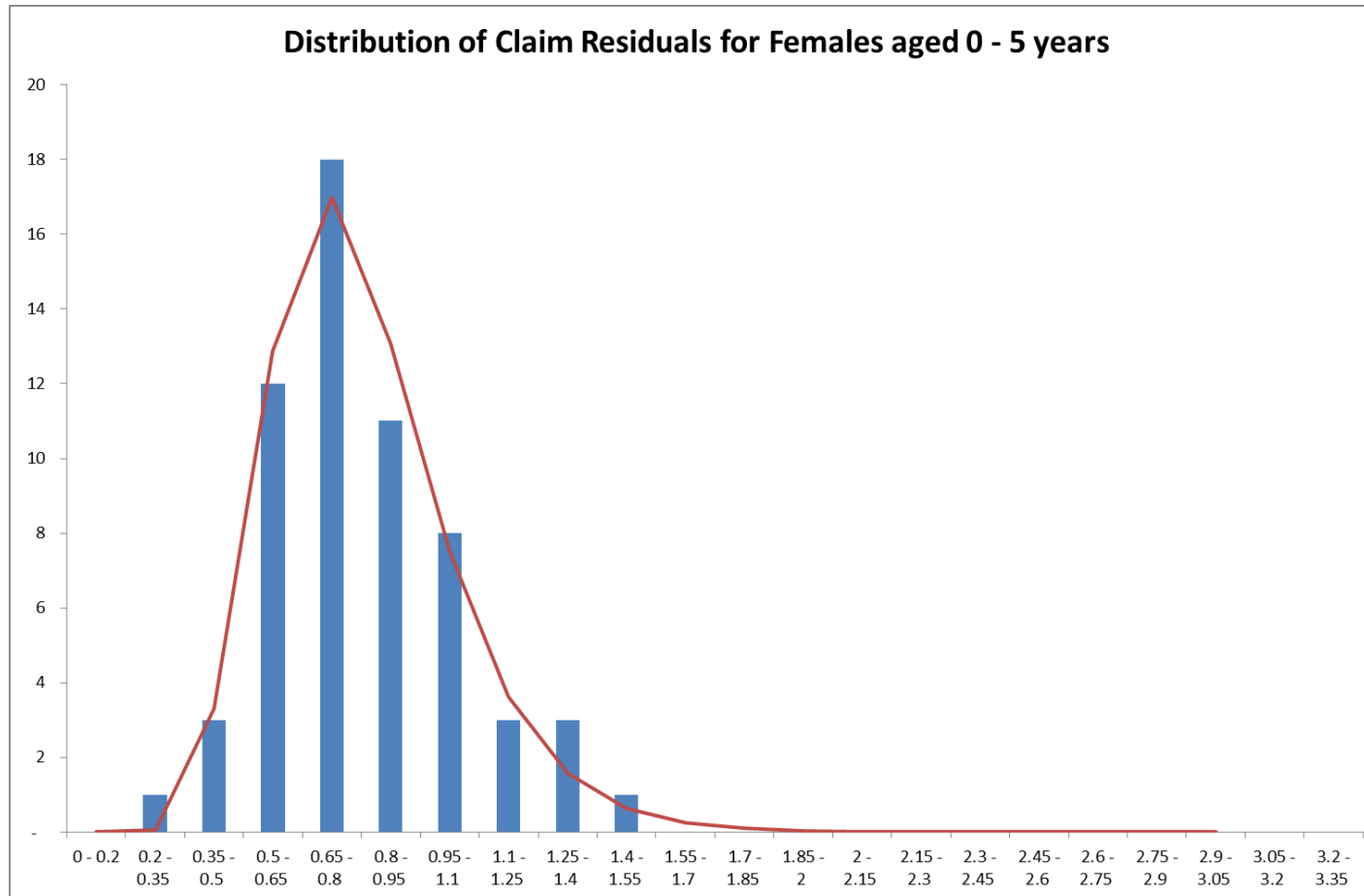
Distribution of residuals by gender and age band



Distribution of residuals by gender and age band



Distribution of residuals for Females aged 0-5 years



Testing residuals for time series effect

- ❖ Auto-regressive model:

$$X_t = c + \sum_{i=1}^p \varphi_i X_{t-i} + \varepsilon_t.$$

- ❖ Moving average model

$$X_t = \mu + \varepsilon_t + \sum_{i=1}^q \theta_i \varepsilon_{t-i}$$

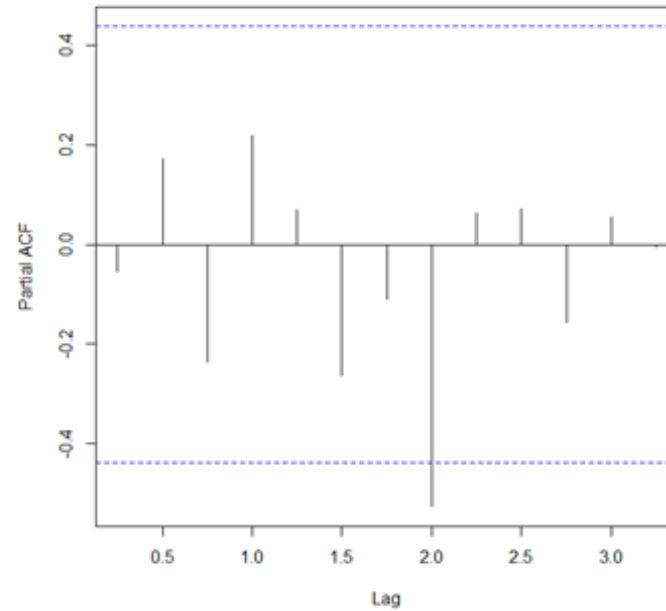
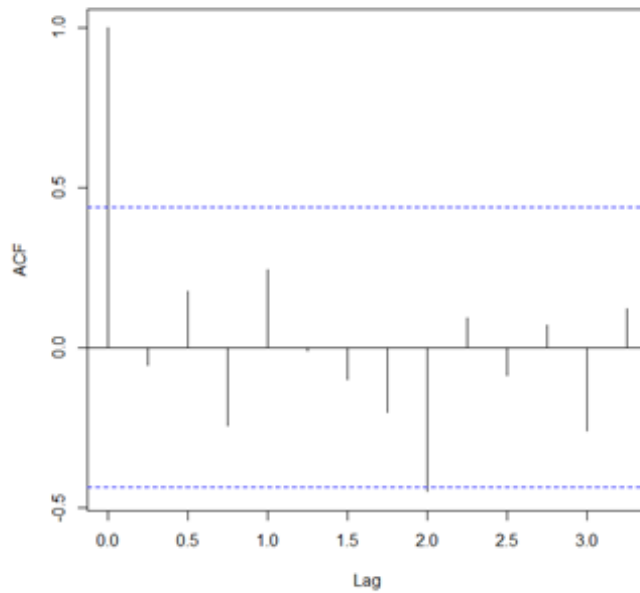
- ❖ Auto-regressive integrated moving average model

$$X_t = c + \varepsilon_t + \sum_{i=1}^p \varphi_i X_{t-i} + \sum_{i=1}^q \theta_i \varepsilon_{t-i}.$$

Some time series concepts

- ❖ Autocorrelation function (ACF): correlation between time series at current point and n lags prior
 - ❖ Negative 1st order autocorrelation: a high value at time 1 predicts a lower value at time 2, i.e. bad Q1 indicates better Q2 etc.
 - ❖ Positive 1st order autocorrelation: a high value at time 1 predicts a higher value at time 2, i.e. bad Q1 indicates bad Q2 as well
- ❖ Partial autocorrelation function (PACF): correlation between time series at current point and n lags prior, net of the effect of previous lags
- ❖ If:
 - ❖ ACF decays (dies down) and PACF cuts off after p lags $\rightarrow$ AR(p) process
 - ❖ ACF cuts off after q lags and PACF decays (dies down) $\rightarrow$ MA(q) process

Testing for auto-regression



Simulation modelling

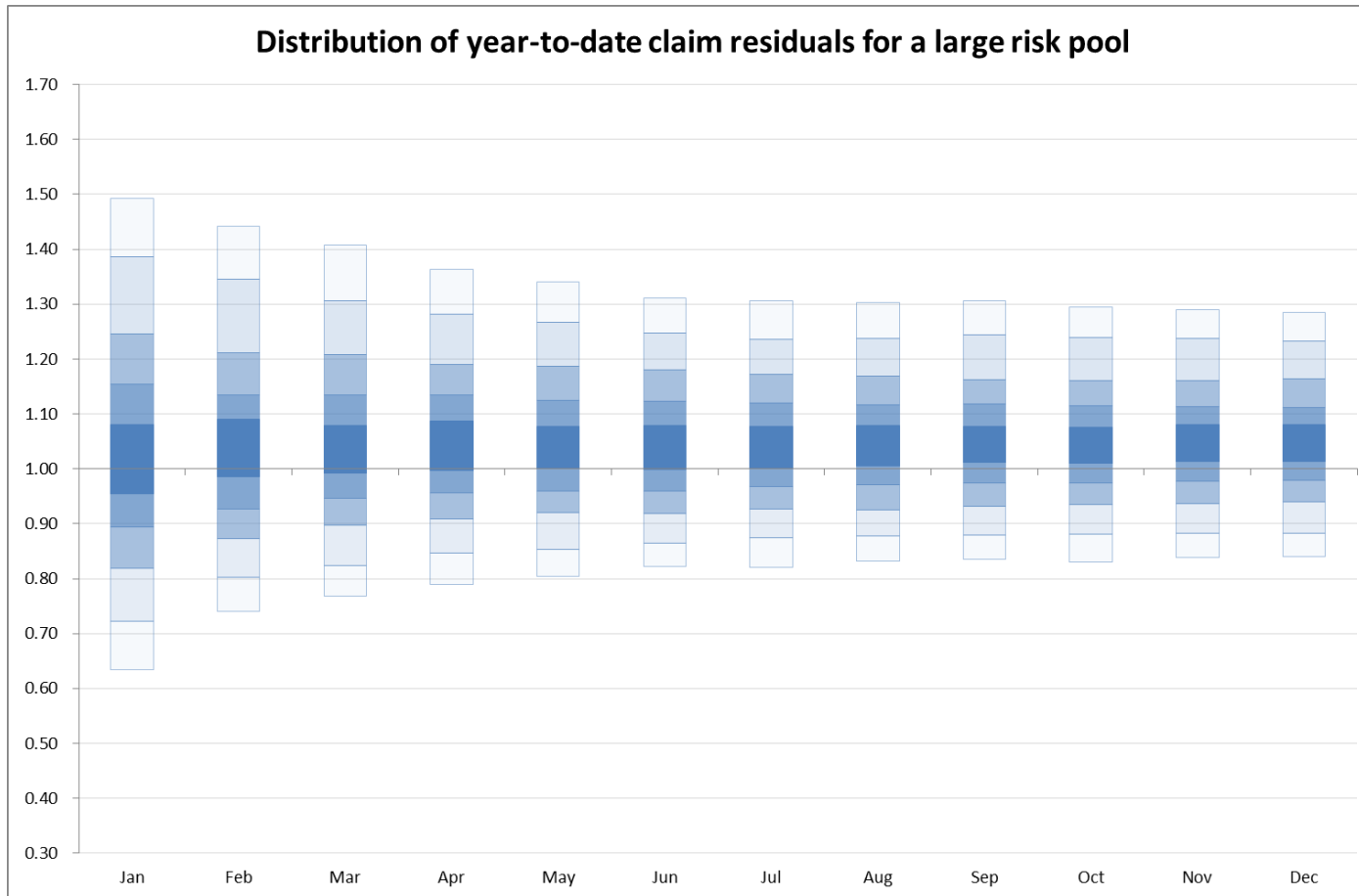
❖ Modelling of budget variance:

- ❖ Year-to-date hospital claims variance modelled
- ❖ Claims variance measured against Budget
- ❖ Budget set using prior year 6-months experience

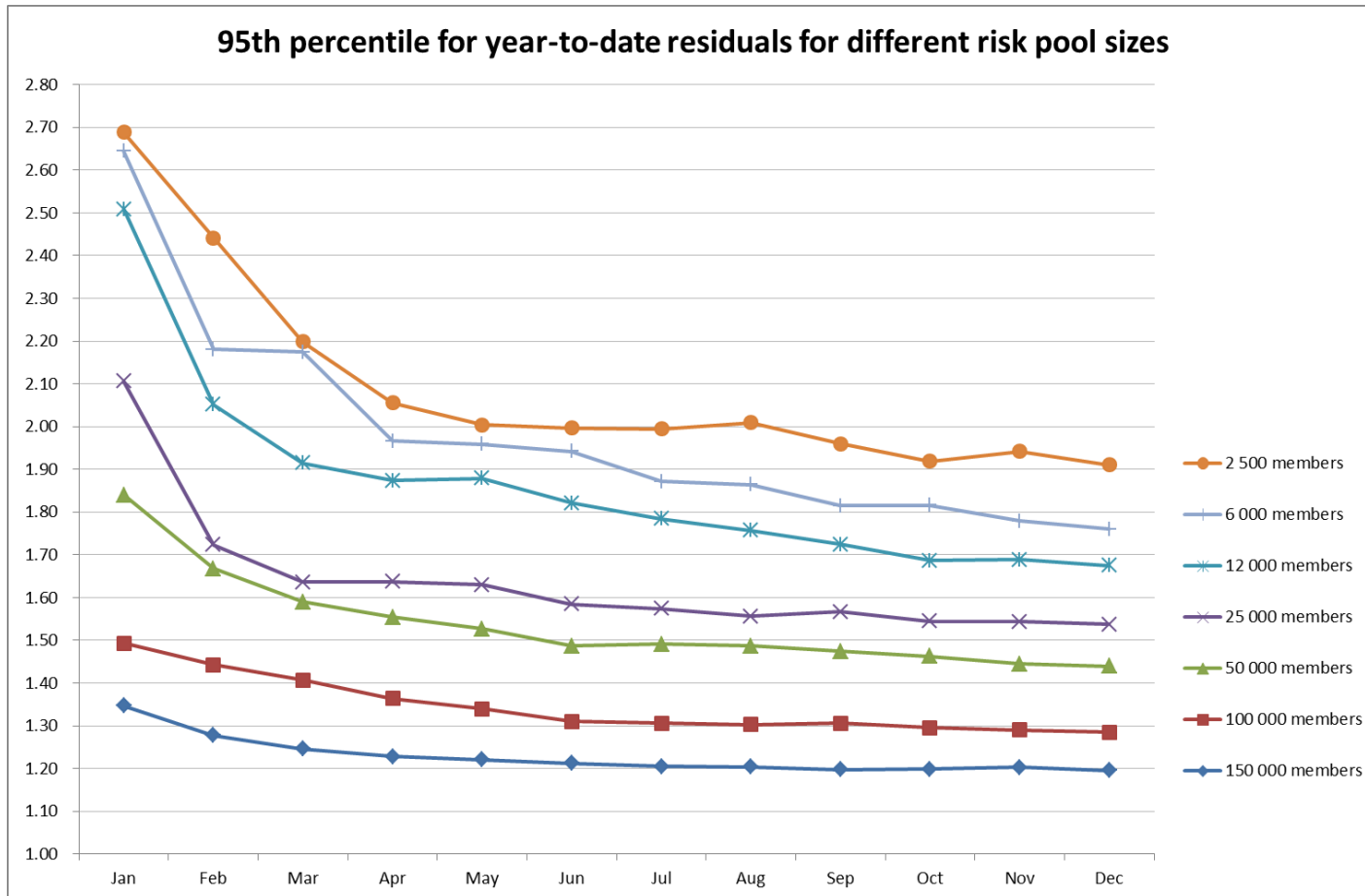
❖ Modelling approach:

- ❖ Monte Carlo simulation approach
- ❖ Assuming a standardised risk pool
- ❖ Log-normal distributions fitted for claim distributions for different risk pool sizes

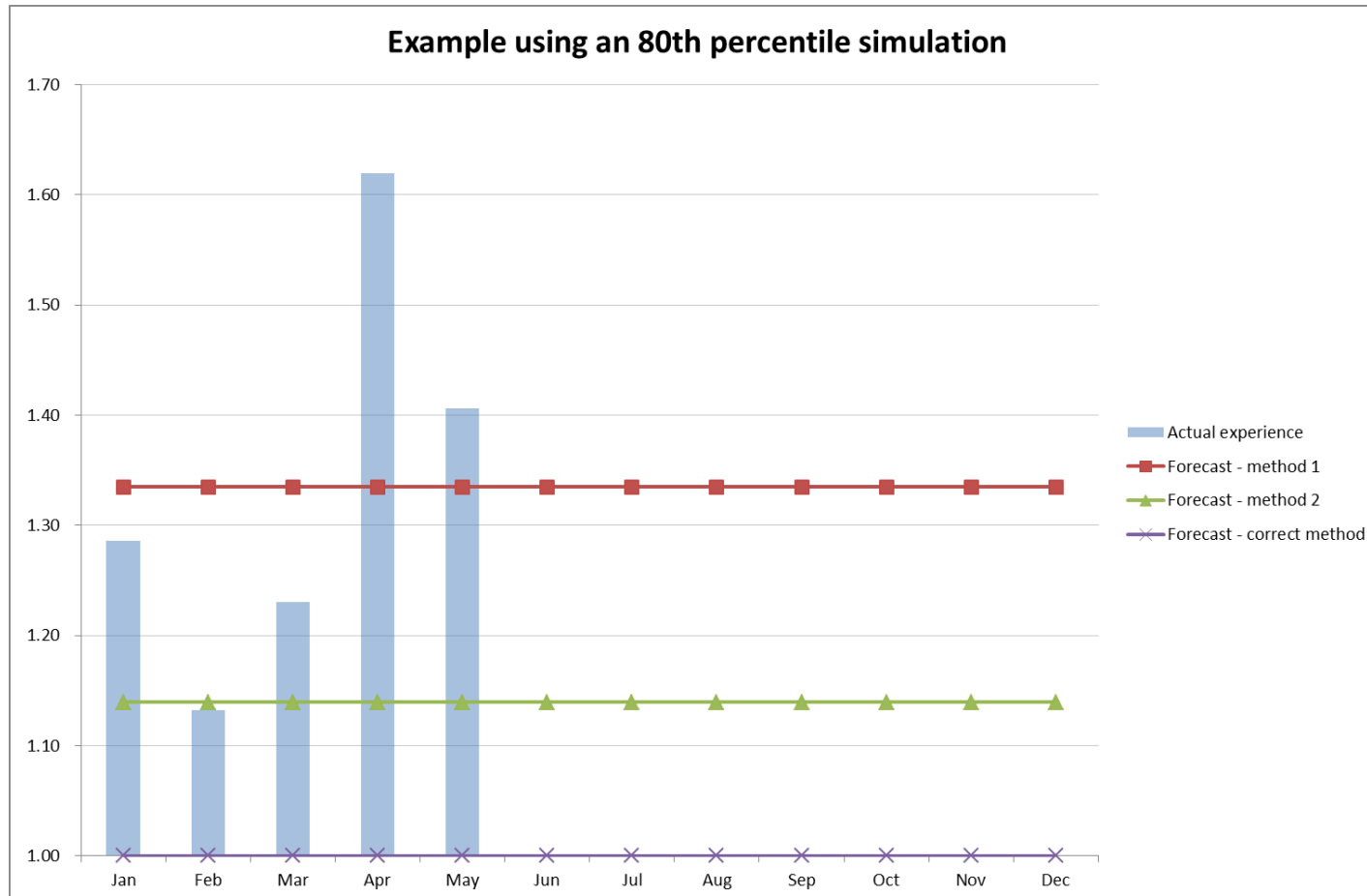
Distribution of year-to-date claim residuals



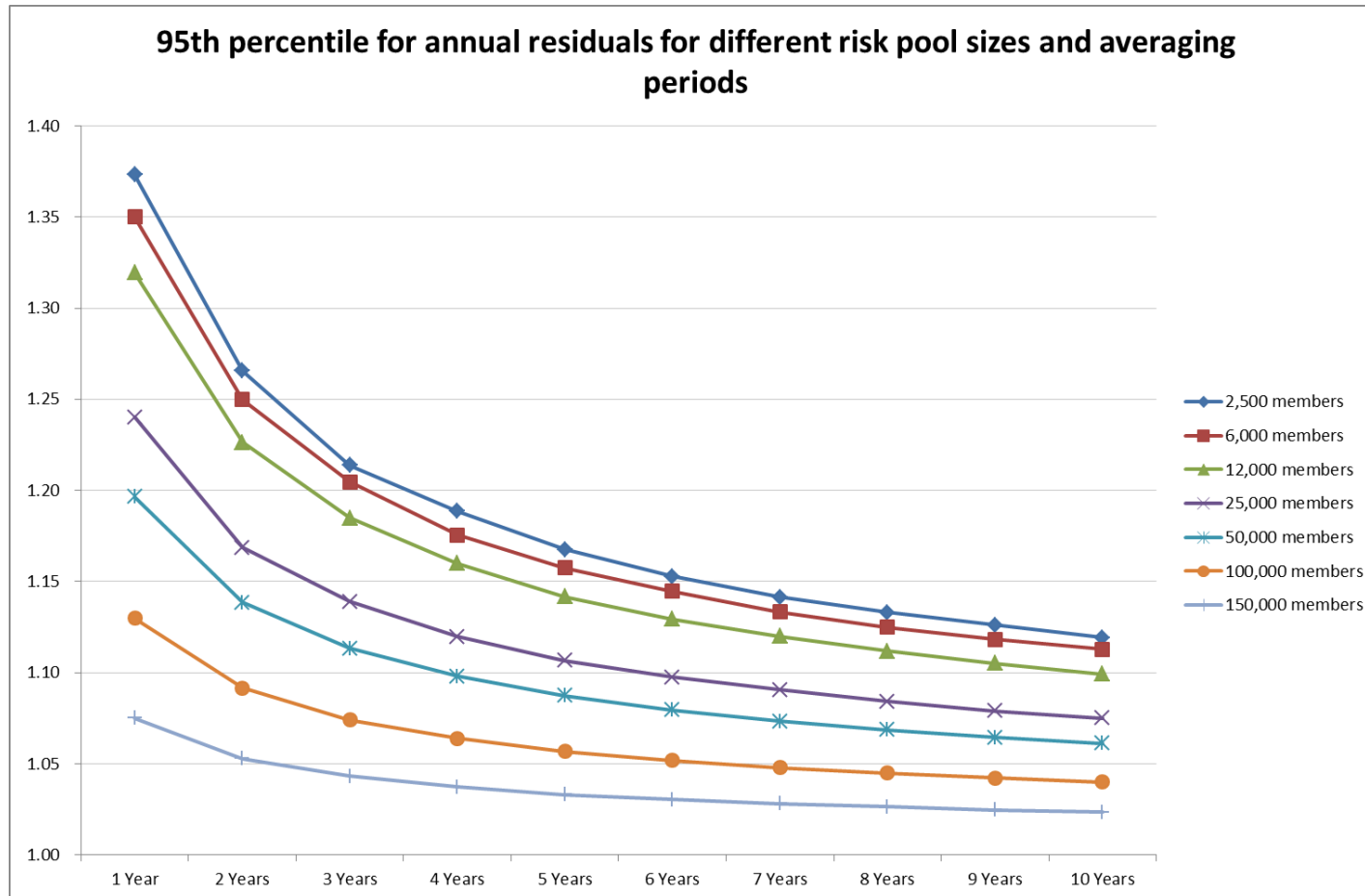
Distribution of year-to-date claim residuals for different risk pools



Claim forecasting methods



Distribution of annual claim residuals for different averaging periods



Lessons so far

❖ Claims forecasting:

- ❖ Important to remove hospital claim residuals from latest experience before forecasting claims

❖ Claims reporting:

- ❖ Case could be made for implementing a claims smoothing reserve for higher cost hospital cases
 - ❖ First quarter results
 - ❖ Full year results (smaller risk pools)

❖ Scheme reserving:

- ❖ Claims smoothing reserve could operate in the same manner as the investment revaluation reserve (for smaller risk pools)

