

NON-PARAMETRIC TOLERANCE INTERVALS FOR SMALL SAMPLE SIZES

An empirical likelihood approach

Agenda

1 Motivation

1.1 Tolerance Intervals? | 1.2 Problems and Approach

2 Methodology

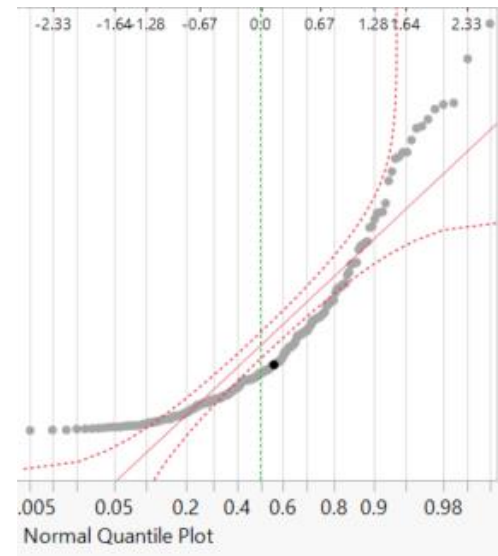
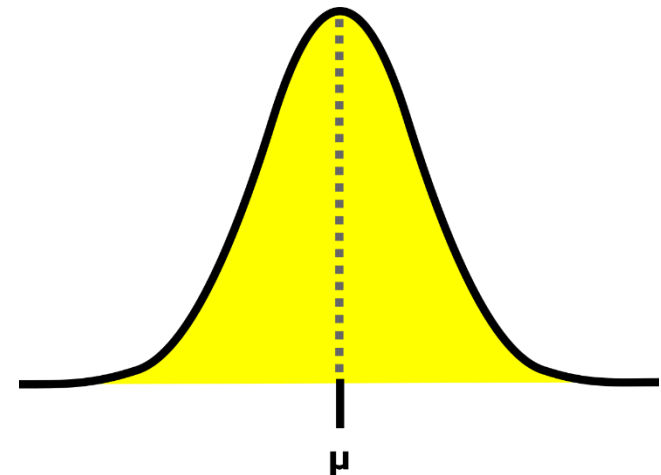
2.1 Existing Methods | 2.2 Extension | 2.3 Performance

3 Implementation in JMP

3.1 Scripting | 3.2 Showcase

Tolerance Intervals

- Why Tolerance Intervals?
 - Upper limit for failures
 - Statement about (almost) all future observations
- Why non-parametric?
 - Normal distribution is common but not universal
- Why small samples?
 - Generating data can be costly
 - Destructive tests are necessary



Problems

Demonstration in JMP

Problems: Summary

- Tolerance Intervals
 - Unable to calculate non-parametric tolerance Intervals for small sample sizes
- Idea: Calculate confidence intervals for quantiles.
 - Non-parametric approach from JMP: empirical likelihood
 - Problem: Confidence are not usable for extreme Quantiles and small sample sizes

Approach

- How does smoothed empirical likelihood Work?
 - Are there different methods?
- How does JMP calculate the confidence Intervals?
- Is there a way to eliminate the problems with small sample sizes and extreme Quantiles?

Existing Methods

- Empirical likelihood was first introduced by Owen (1988)
- When quantiles are considered, the log likelihood is dependent on the empirical distribution function F_n (Adimari, 1998):

$$l(\Theta) = 2n \left[F_n(\Theta) \log\left(\frac{F_n(\Theta)}{q}\right) + (1 - F_n(\Theta)) \log\left(\frac{1 - F_n(\Theta)}{1 - q}\right) \right]$$

- Confidence intervals can be calculated by using Wilks theorem Owen (1988): $\lim_{n \rightarrow \infty} P(l(\Theta) \leq c) = P(\chi_1^2 \leq c)$
- Several methods of smoothing exist:
 - Smoothing using a kernel function. (Chen, Hall, 1993) (JMP)
 - Linear smoothing of F_n (Adimari, 1998)

Comparison. Median

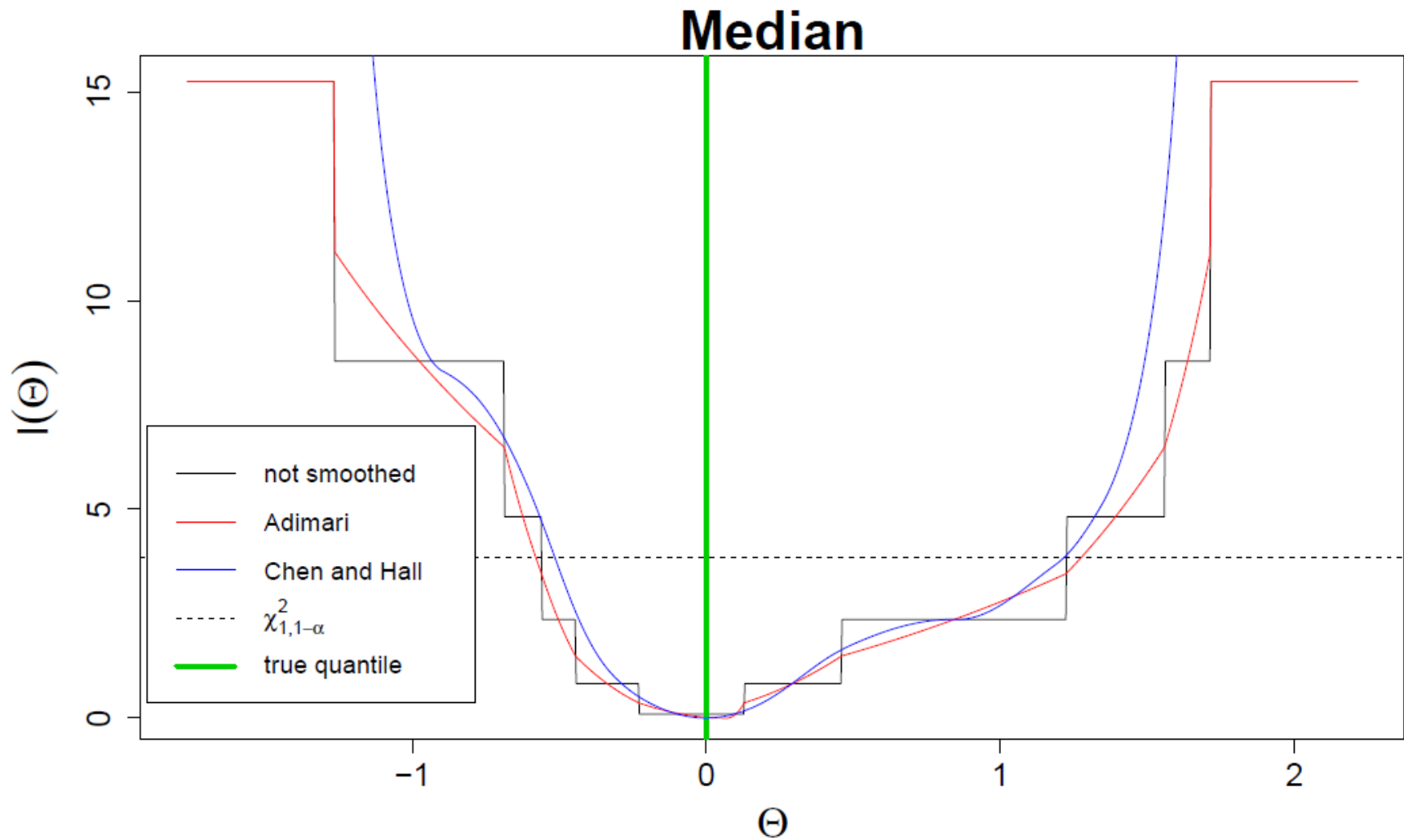


Figure: Smoothed empirical likelihood functions ($n = 11; q = 0.5; \alpha = 0.05$)

Comparison 1%-Quantile

1%-Quantile

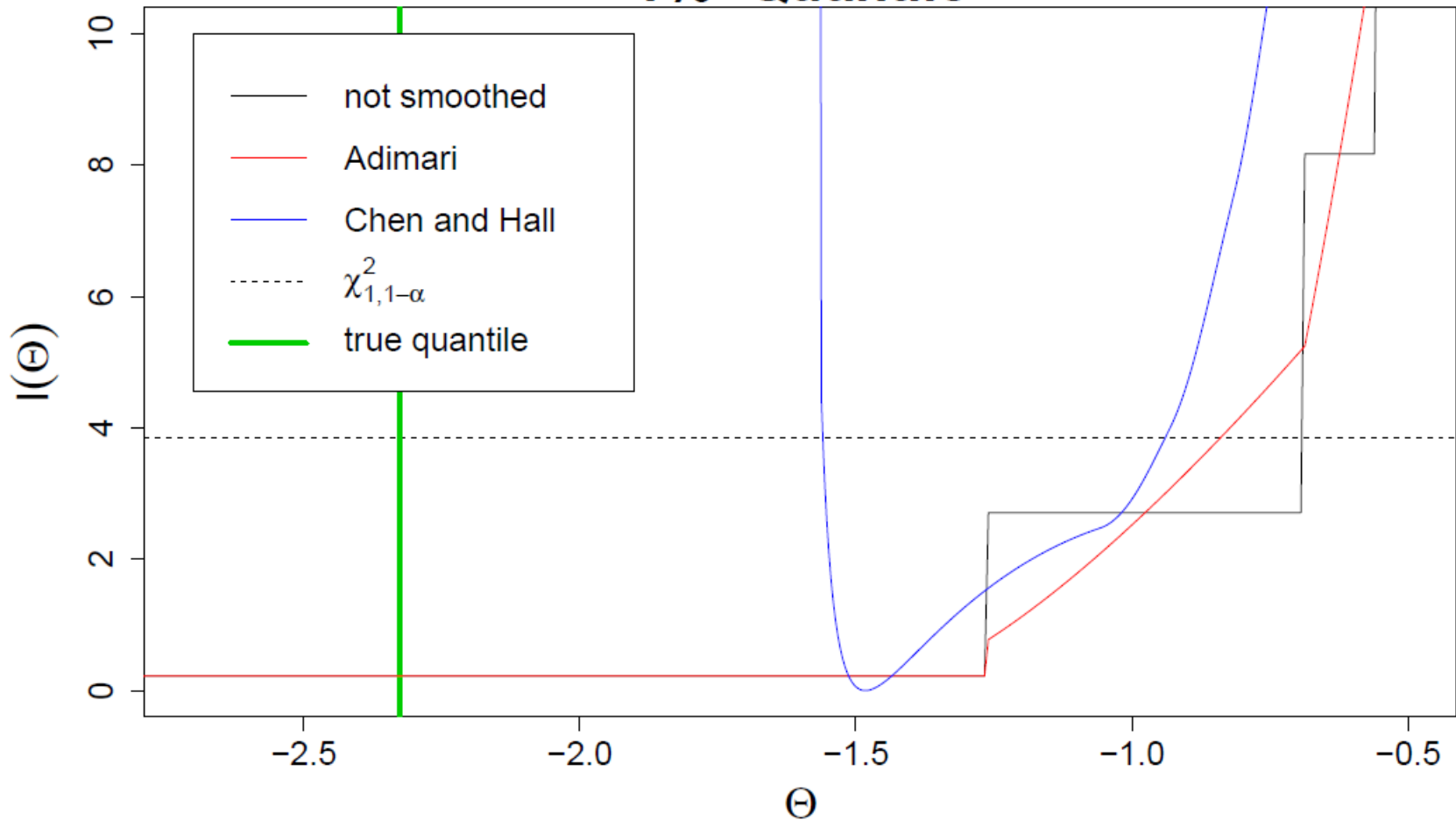


Figure: Smoothed empirical likelihood functions ($n = 11; q = 0.01; \alpha = 0.05$)

Coverage Rates

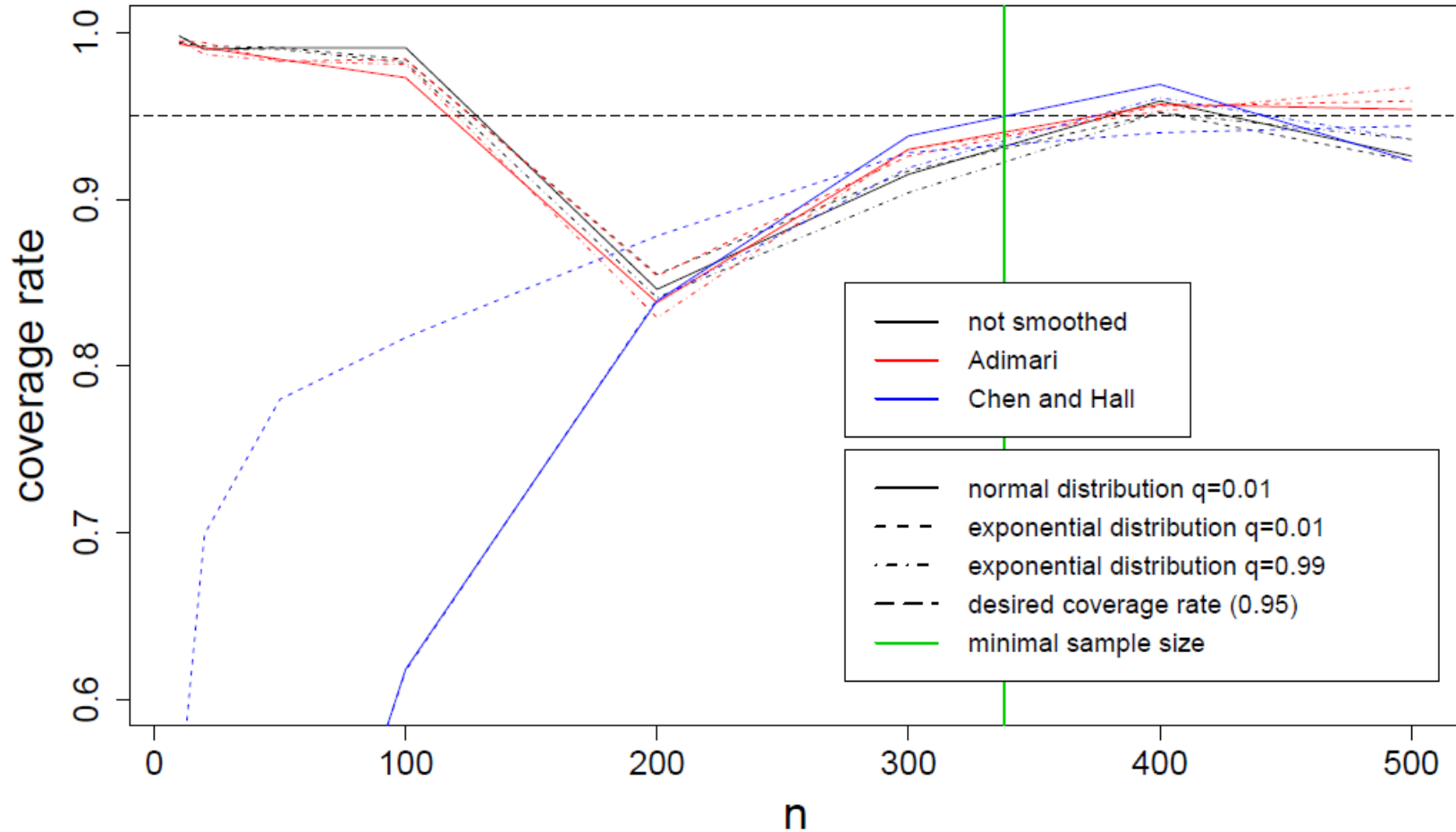


Figure: Estimated coverage rates based on 1000 samples

Linear smoothing

- The smoothing proposed by Adimari (1998) is achieved by using a linear smoothing F^* of F_n :

$$F_n^*(\Theta) = \begin{cases} 0 & \text{if } \Theta < x_{(1)} \\ H(\Theta) & \text{if } \Theta \in [x_{(1)}, x_{(n)}] \\ 1 & \text{if } \Theta \geq x_{(n)} \end{cases}$$

where

$$H(\Theta) = \begin{cases} \frac{2i-1}{2n} & \text{if } \Theta = x_{(i)}; i \in \{1, \dots, n-1\} \\ (1-\lambda)\frac{2i-1}{2n} + \lambda\frac{2i+1}{2n} & \text{if } \Theta \in (x_{(i)}, x_{(i+1)}); \lambda = \frac{\Theta - x_{(i)}}{x_{(i+1)} - x_{(i)}}; i \in \{1, \dots, n-1\} \end{cases}$$

Empirical distribution function

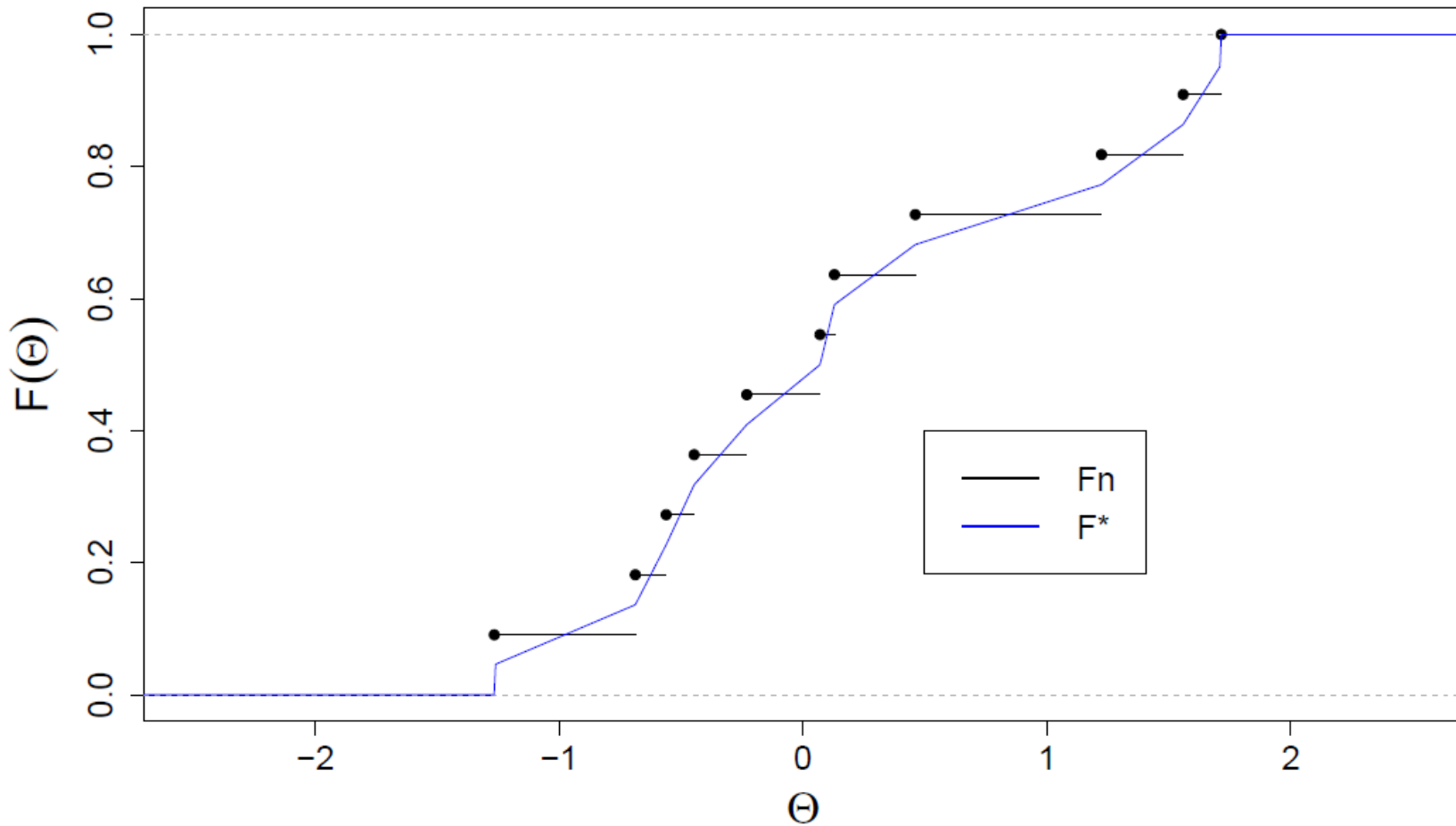


Figure: Smoothing of F_n for 11 observations from a standard normal distribution

Extending the empirical distribution function

- Find an extension of the likelihood function for values outside of the observed data so that
 - finite confidence intervals are guaranteed.
 - the desired coverage rate is achieved.

1. extending F^* as follows:

$$F_{\text{ext}}(\Theta) = \begin{cases} 0 & \text{if } \Theta \leq x_{(1)} - d_1 c \\ \frac{1}{2n} - \frac{1}{2n*d_1*c} (x_{(1)} - \Theta) & \text{if } x_{(1)} - d_1 c < \Theta < x_{(1)} \\ H(\Theta) & \text{if } x_{(1)} \leq \Theta \leq x_{(n)} \\ \frac{2n-1}{2n} + \frac{1}{2n*d_2*c} (\Theta - x_{(n)}) & \text{if } x_{(n)} < \Theta < x_{(n)} + d_2 c \\ 1 & \text{if } \Theta \geq x_{(n)} + d_2 c \end{cases}$$

Where $c \geq 1$; $d_1 = \frac{1}{10} \sum_{i=1}^5 (x_{(i+1)} - x_{(i)})$ and
 $d_2 = \frac{1}{10} \sum_{i=1}^5 (x_{(n-i+1)} - x_{(n-i)})$

2. linear extension of the likelihood function.

Example

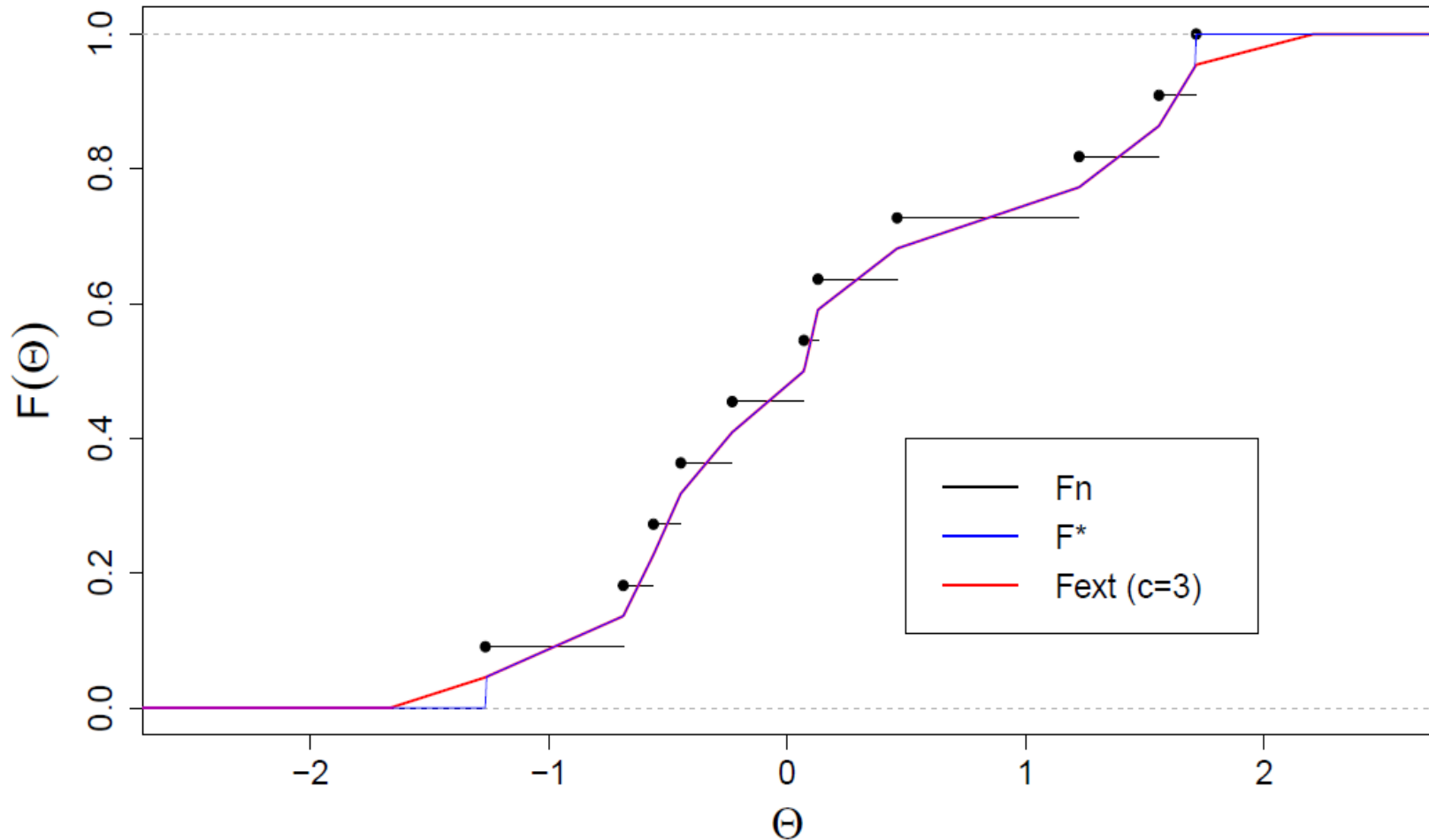


Figure: Smoothing of F_n using F_{ext}

Example

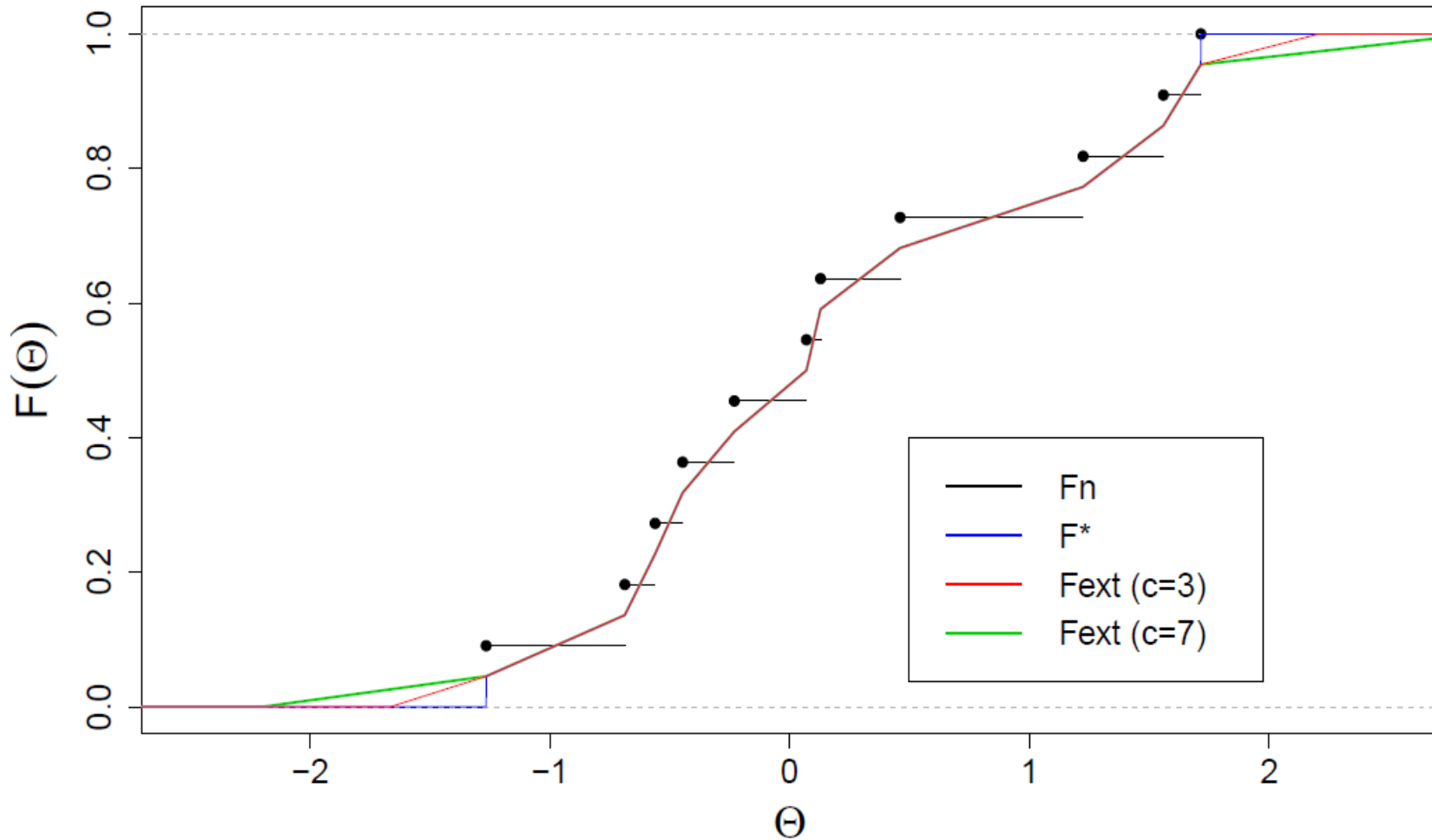


Figure: Visualising the influence of the parameter c on F_{ext}

Example

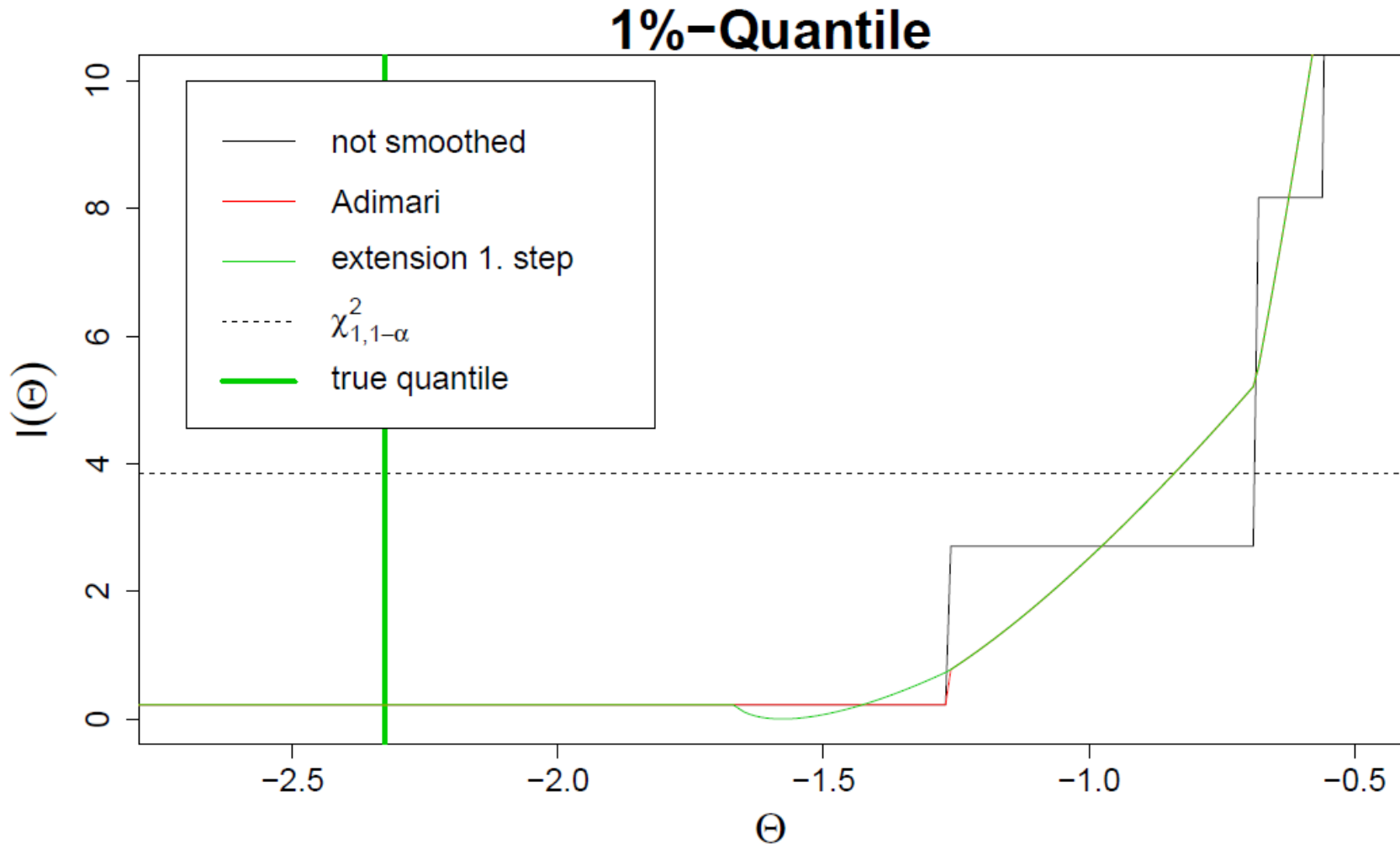


Figure: First step of the extension ($c = 3$)

Example

1%-Quantile

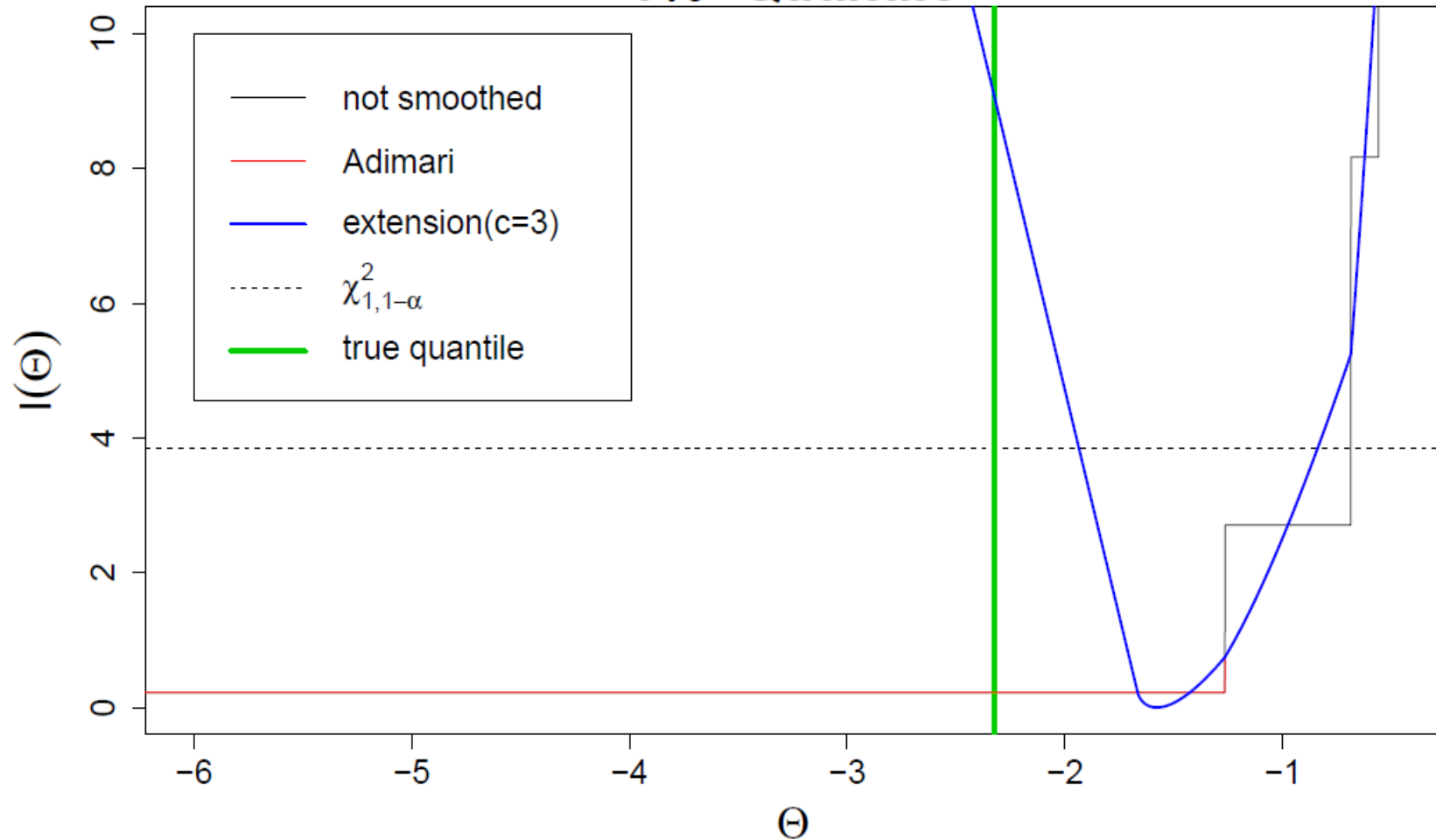


Figure: Second step: further linear extension ($c = 3$)

Example

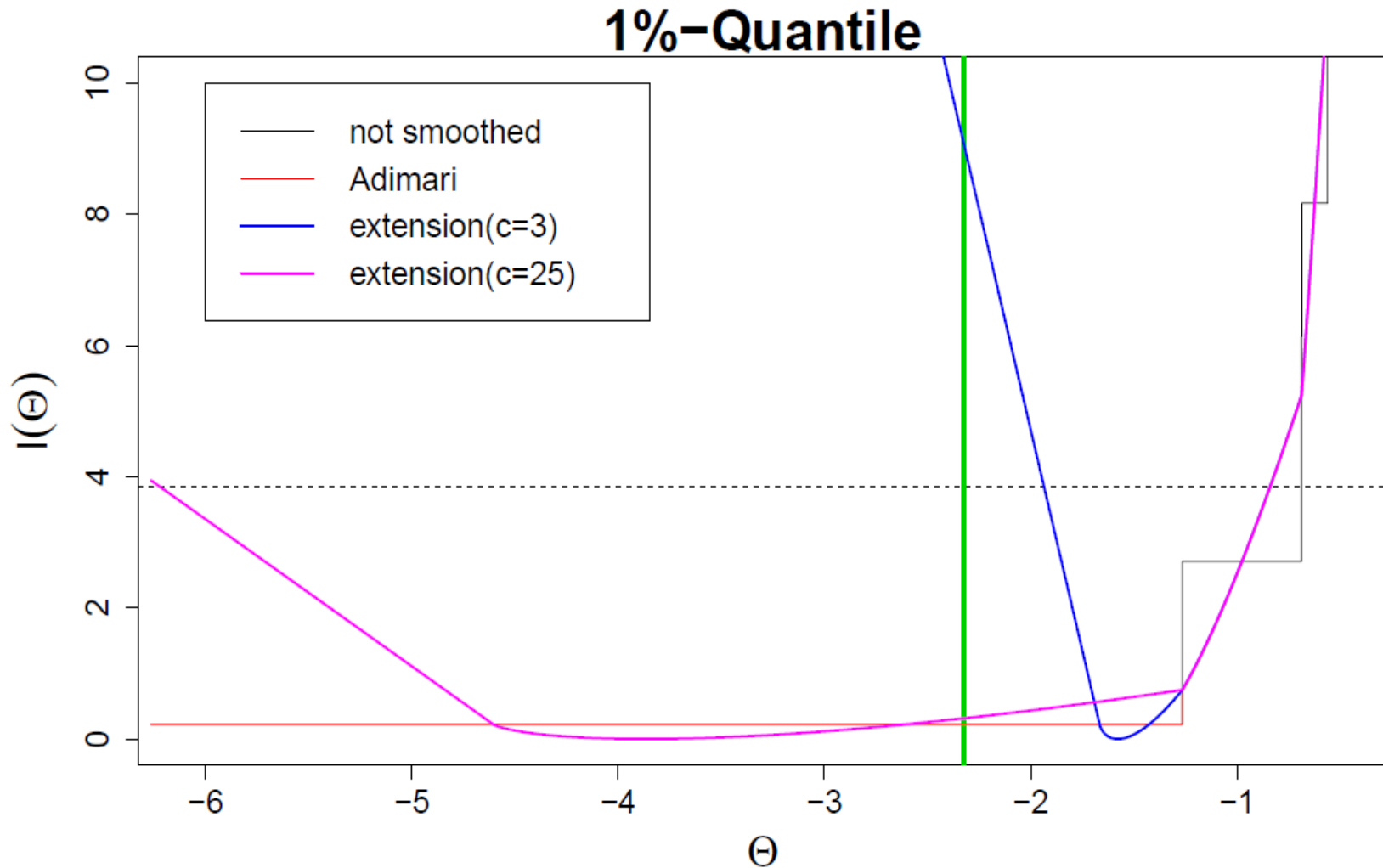


Figure: Fully extended likelihood function for different values of c

Assuring Coverage

- The quality of the Confidence Interval is dependent on the extension parameter c .
- The smallest value of c which results in a coverage rate of at least $(1 - \alpha)$ is desired.
- A simulation study was carried out under the following assumptions:
 - The required value for c depends on q , n , R and α

$$R := \begin{cases} q * n & \text{if } q \leq 0.5 \\ (1 - q) * n & \text{if } q > 0.5 \end{cases}$$

- The required value for c does not depend on the distribution of the data.

Simulation Study

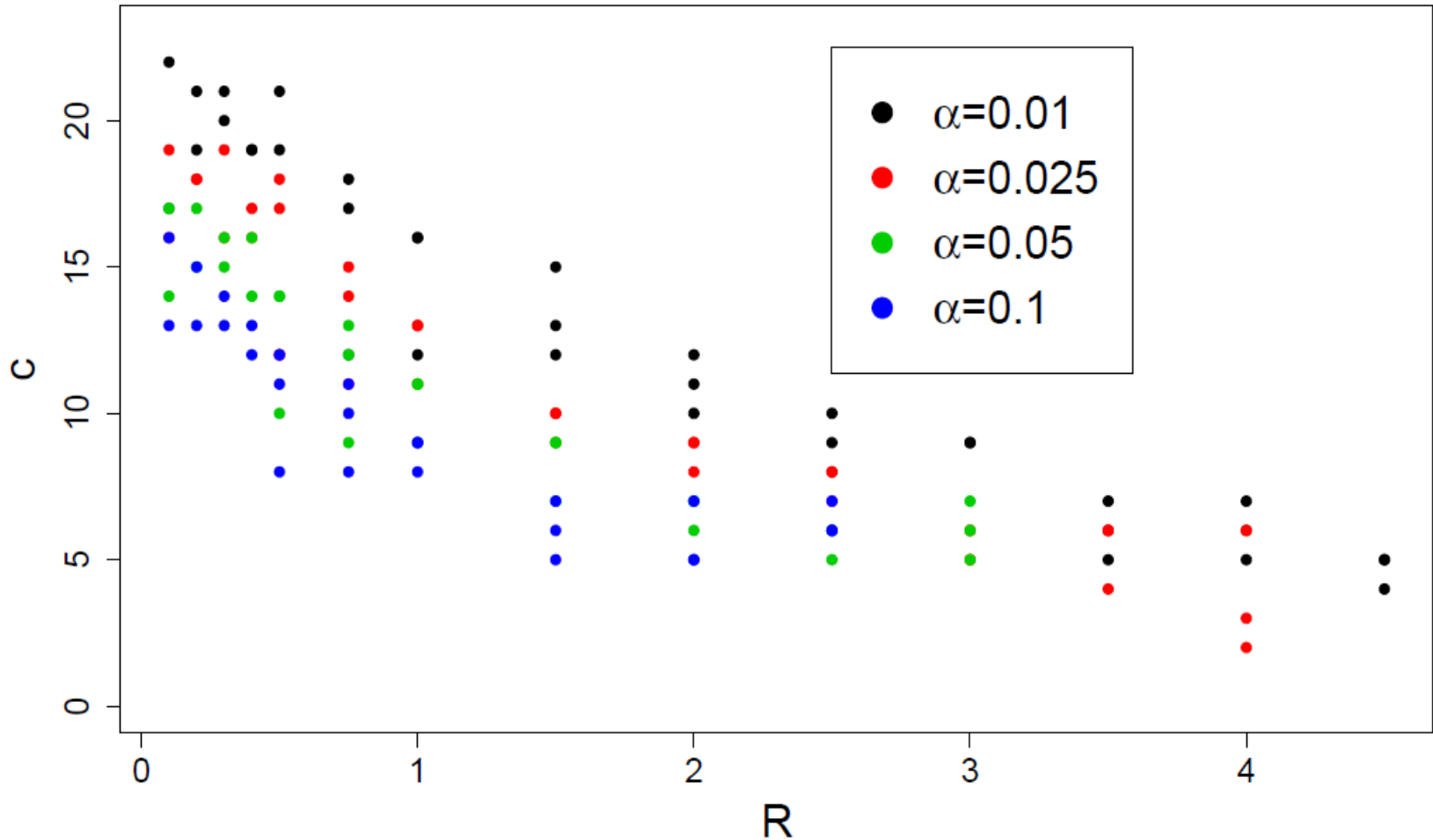


Figure: Chosen value of c for different values of R

Simulation Study

- Model for c : $\hat{c} = 12.344 - 7.082\sqrt{R} - 2.454\log(\alpha) - 75.125q - 0.004n$
- Adjusted $R^2 = 0.933$

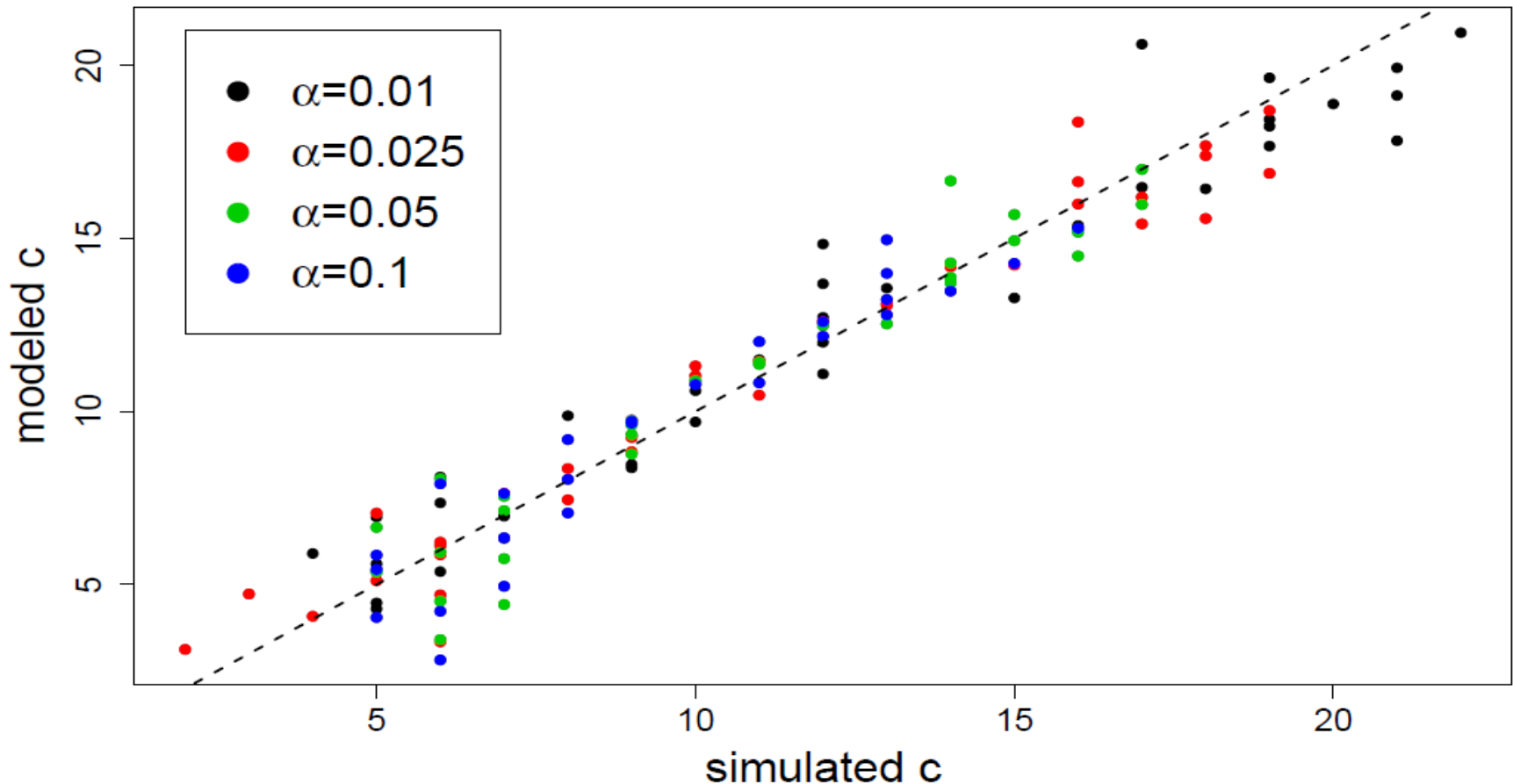


Figure: Visualising the Model

Example

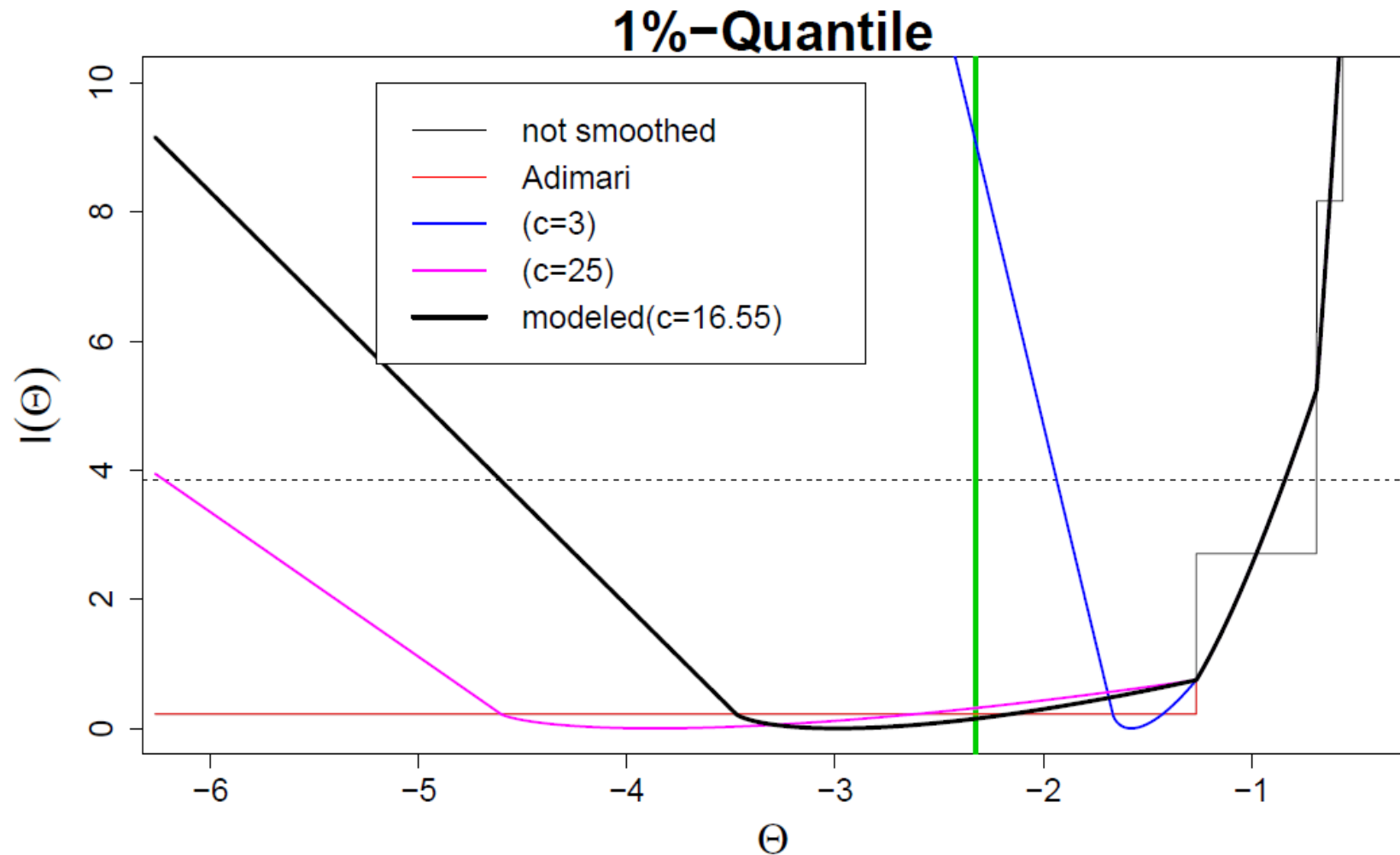


Figure: Example for the modeled value of c ($n = 11, q = 0.01, \alpha = 0.05$)

Coverage Rates

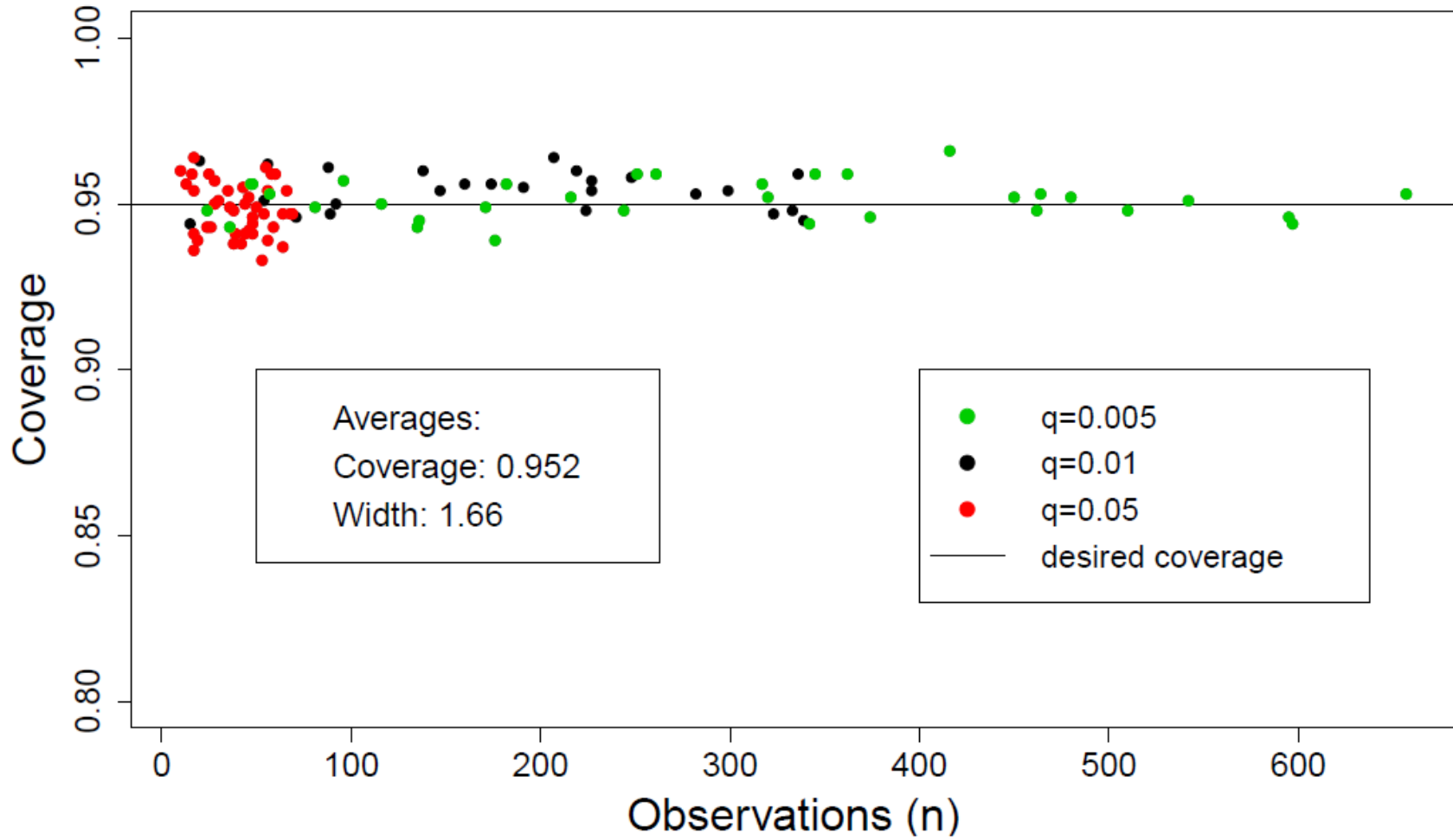


Figure: coverage rates based on 1000 samples for normally distributed data

Coverage Rates

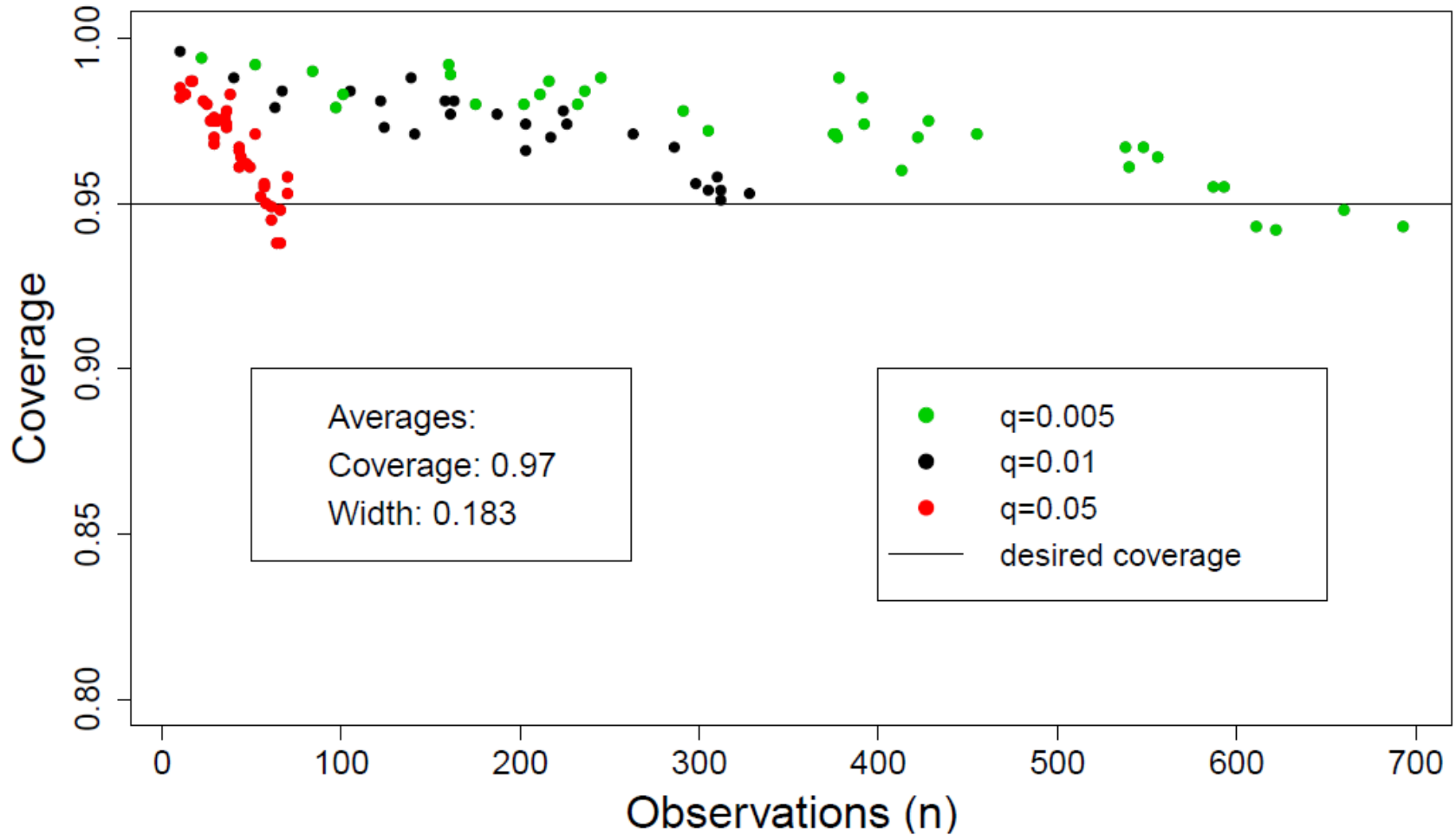


Figure: coverage rates based on 1000 samples for exponentially distributed data

Coverage Rates

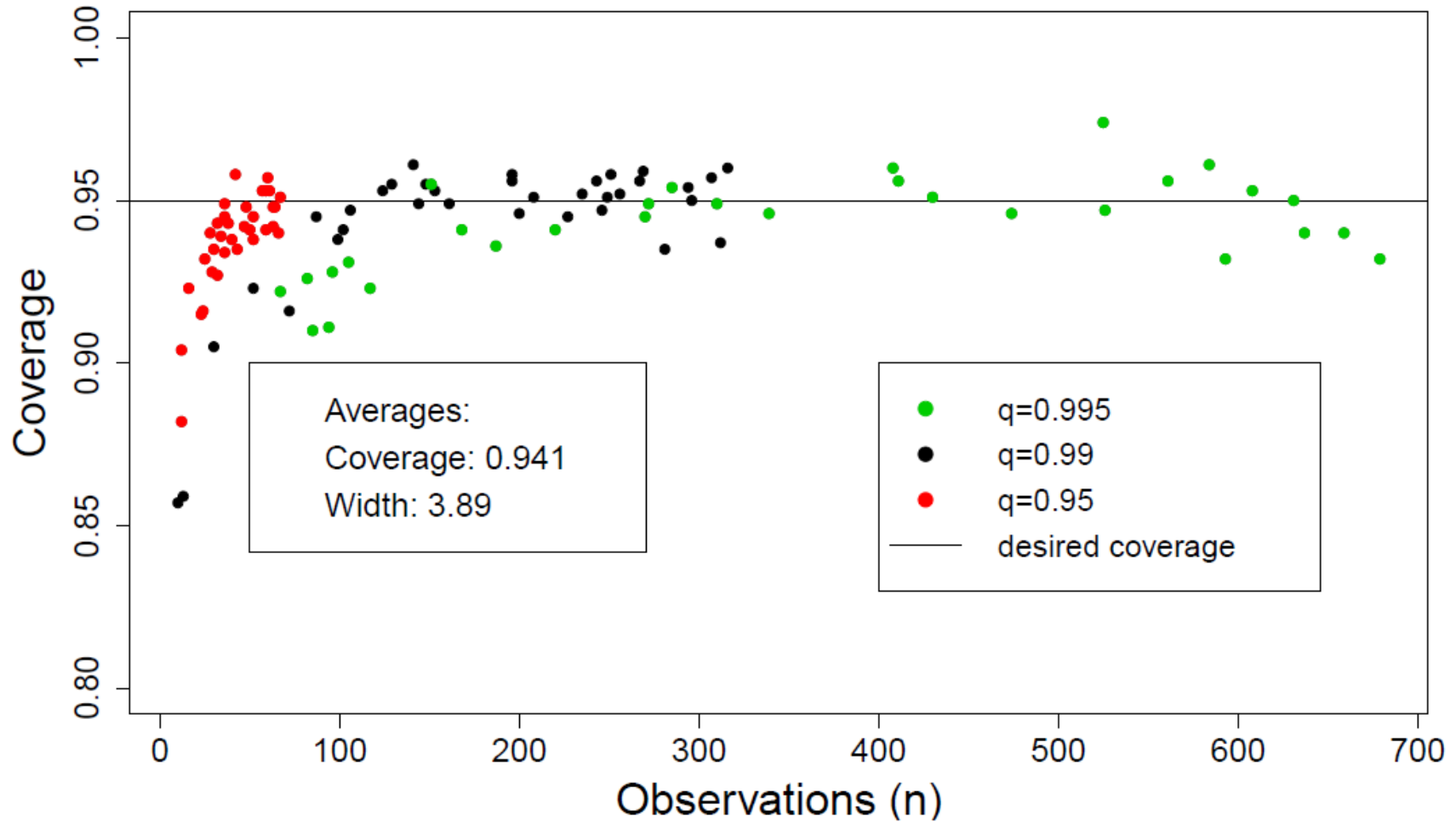


Figure: coverage rates based on 1000 samples for exponentially distributed data

Problems and Solutions

- The required value of c is not depended on the distribution of the Data
- However, a vast improvement compared to the existing methods is achieved.
 - Drop in quality for data with very light/ heavy tails
- To further improve the method, a semi parametric approach is proposed:
 - Assume a distribution of the data and develop a model for the extension parameter using that distribution
 - Example: Exponential distribution

Modelling different distributions

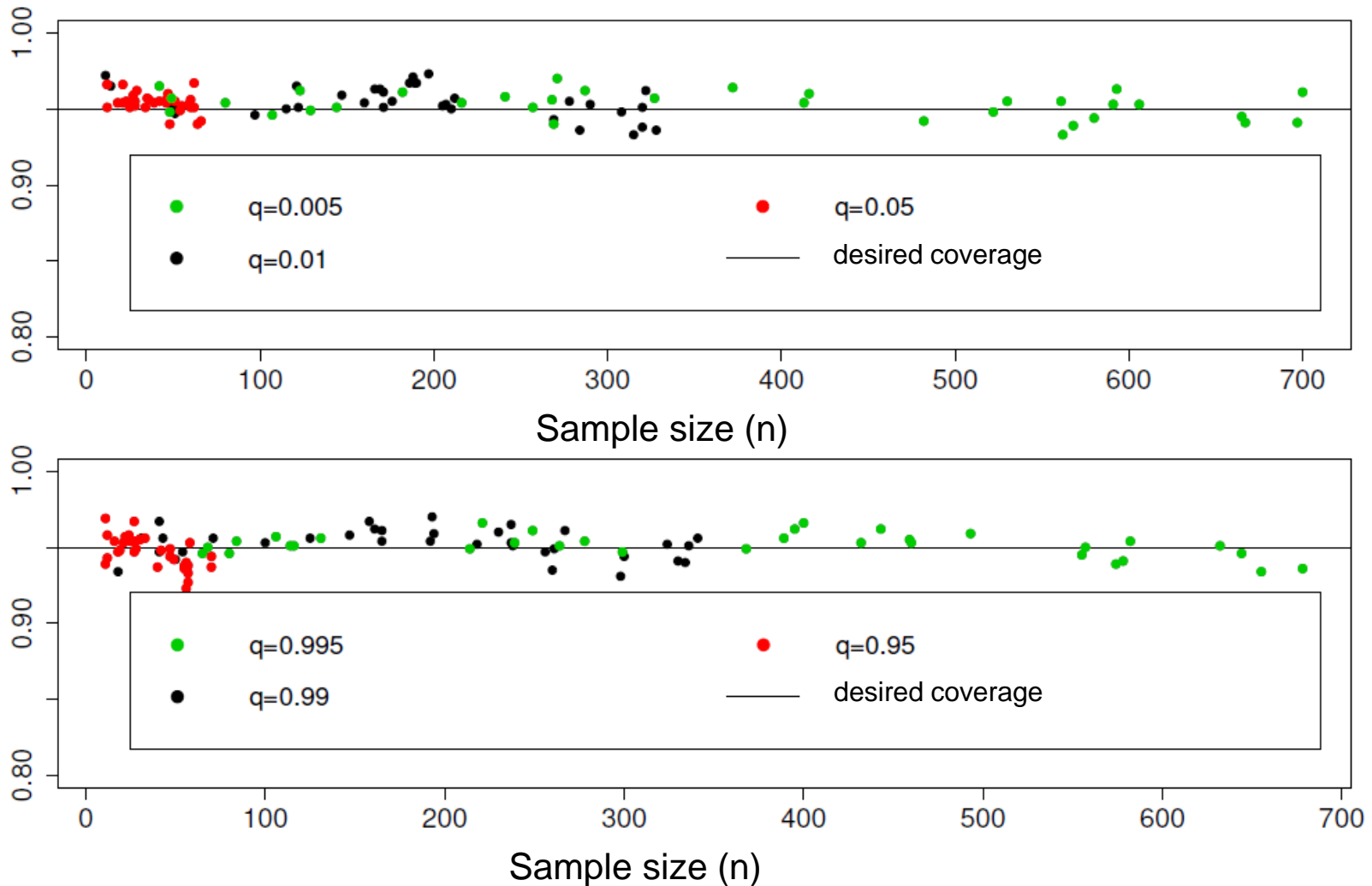


Figure: coverage rates based on 1000 samples for exponentially distributed data

Implementation



Demonstration in JMP

Implementation: Summary

- Straight forward programming of the functions and models
- Difficulty: Finding an algorithm for the borders of the CI
 - Minimize function: Fast but unstable in some situations
 - Simple self-made algorithm: slower but stable
- Development of a simple JMP application for user friendliness.