UCLouvain

FACULTE DES SCIENCES

Faculté des sciences

Strong versus weak prior for predicting patient recruitment at the start of clinical trials in the context of drug availability issues

Auteur: Clément Laloux

Promoteurs: Catherine Legrand & Marco Munda

Lecteur: Vincent Bremhorst

Année académique 2019-2020

• Annexes

6.1 Annexe 1. R function to conduct the simulations

As we mentioned in the **Discussion**, this R function performs the analysis we conducted, that is, comparing the performances of several priors given specifics settings that must be specified by the user (e.g. a planned duration error). Below, we explain in detail how it works. For code specifics, see the comments directly in the R code, which is available as an annexe of this work. Noteworthy, the use of the function is highly specific to the settings and some arguments cannot be computed easily as it will be explained below.

Before the function, it is important to define the Stan code to generate a draw from the posterior distribution. The code follows the specific Stan syntax. It was put prior to the function for two reasons (i) it is time consuming to transform the code from Stan syntax to R and (ii) this enables to modify easily the code to include different distributions in the prior or the likelihood. In the code below, we encoded all the data, parameters and distributions relative to our models, for their understanding, we invite you to visit the Stan website[4].

After setting the Stan code, we could define the function. The function includes ten arguments, which are briefly described below:

- *n_sim*: Number of simulation to be run, i.e. the simulated data that mimic real clinical trials.
- *real_t_tot*: The theoretical duration of the simulated trials.
- *n*: The number of patients to be recruited.
- *Start_date*: The start date of the trials to be able to compute the distributions of arrival per month.
- *m*: the number of subjects already in the study at the time of the predictions (no limit on the number of values, but the greater they are, the longer it will take to run the function).
- *n_pred*: the number of waiting times to be generated in the predictions.
- *diff_month*: the planned duration error, i.e. the difference in months between real trials and expected duration.

[4] https://mc-stan.org/

- *V_lambda*: the levels of information considered (no limit on the number of values, but the greater they are, the longer it will take to run the function).
- *Time_points*: The length of the interval between time points for predictions
- *Median_precision*: The method to compute the median precision (either the Mean squared error (MSE) or the Mean absolute error (MAE)

The function is composed of three parts. The first part aims at generating the simulated data that mimic real clinical trials. The second part aims at defining the tables that will store the global results over all simulations. The third part consists in the computation of the results. Below, we described how each part works and which arguments are involved.

For the first part, all the simulations are generated in the same loop so that if one wants to obtain constant simulations over different planned duration error, it just has to specify a *set.seed()* before running the function. The arguments involved are *n_sim*, *real_t_tot*, *n* and *Start_date*.

For the second part, three global results are returned by the function in a list:

- The mean HDI width over the *n_sim* simulations (second element of the list).
- The mean MSE (Mean Square Error) or MAE (Mean Absolute Error) over the *n_sim* simulations, you can select between both in the *Median_precision* argument (third element of the list).
- The proportion correct coverage over the *n_sim* simulations (fourth element of the list).

Moreover, the function also returns the results computed in each simulation (first element of the list).

The third part consists in the computation of the results. It consists in two nested loops. The first level over the variances introduced in *V_lambda* and the second level over the m values introduced in *m*. Three other arguments are used in this part of the code, *diff_month*, *n_pred* and *Time_points*. The use of the first one is pretty straightforward, however, for the two others, some explanations need to be provided.

Regarding *n_pred*, it must be high so that enough patients are generated to compute the results at all time points for predictions. Indeed, in some cases, the time points for predictions are larger than the expected duration. Therefore, we must generate a number of patients that is large enough to make predictions beyond this expected duration. To illustrate this, let’s say we want to know the prediction accuracy of a prior at 10 months in a setting with $T_{theoric}$=20 and *diff_month*=12. In this case, the expected duration would be 8 months. Hence, to be able to assess the prediction accuracy at 10 months, we need to generate more than n patients. Overall, *n_pred* need to be larger than n-m and must be chosen so that the number of months of recruitment is larger than the time points for prediction. For example, in a setting with n=500 and $T_{theoric}$=20, *n_pred* value was 900 so that even with *diff_month=12*, we were able to assess prediction accuracy at 10 months. The main issue with *n_pred* is that we have no method to compute it automatically, as it is highly specific to the values of *real_t_tot* and *n* used. Some tests must be done prior to the function to ensure the value chosen is appropriate.

Regarding *Time_points*, it represents the length of the interval between time points for predictions. They are always 5 times points. It must be chosen so that the time points never exceed *real_t_tot*. Otherwise the function stops. Unfortunately, as above, no automatic method exists to verify the values is appropriate and some tests need to be run.

Eventually, by running the two loops, which can take some times (more than 1 day for a setting with *n_sim=1000*, *real_t_tot=48*, *n=48* and *n_pred=1100* involving 6 variances and 6 m values), it yields all the results presented above in a list. As we explained, this part is the most complex of the function, because values for *n_pred* and *Time_points* cannot be computed in the function and must be defined before.

6.1.1 R Code

```
# LSTAT2820 - Mémoire
# Programmation en R
# 2019/2020
# Mémoire
# By Clement Laloux

# Clear Working Directory
rm(list = setdiff(ls(), c()))

# Library ####
library(invgamma)
library(rstan)
# Time data type
library(lubridate)
library(timeDate)
# Highest posterior density interval
library(HDInterval)

# Set Working Directory ####
wd <- ""
setwd(wd)
rm(wd)

# Stan model definition ####
# Define the Stan model to draw a sample of the posterior distribution of lambda
Analyse_Prior_Stan = "
data{
int<lower = 0> N;         // size of the dataset used
real y[N];                // y = InterArTm (except 0 value)
real<lower = 0> alpha_p;            // Prior on alpha for the inverse gamma distribution
real<lower = 0> beta_p;             // Prior on beta for the inverse gamma distribution
}
parameters{
real<lower = 0> lambda;    // parameter of the exponential distribution
}
model{
lambda ~ inv_gamma(alpha_p, beta_p); // Prior on lambda

for (i in 1:N)
{
  target += exponential_lpdf(y[i]|1/lambda); // No censored data, only density function
}
```

```
}"
# Transform the Stan code to be used in R then save it in an RDS file to save computational
time
#Analyse_Prior_R = stan_model(model_code = Analyse_Prior_Stan)
#saveRDS(Analyse_Prior_R, paste0("Analyse_Prior_R", ".rds"))
Analyse_Prior_R = readRDS("Analyse_Prior_R.rds")

# Simulation studies ####
# n_sim: Number of simulation to be run, i.e. the simulated data that mimic real clinical trials.
# real_t_tot: The theoretical duration of the simulated trials.
# n: The number of patients to be recruited.
# Start_date: The start date of the trials to be able to compute the distributions of arrival per
month.
# m: the number of subjects already in the study at the time of the predictions. There is
#    no limit on the number of values, but the greater they are, the longer it will take to run the
function.
# n_pred: the number of waiting times to be generated in the predictions.
# diff_month: the planned duration error, i.e. the difference in months between real trials and
expected duration.
# V_lambda: the levels of information considered. There is no limit on the number of values,
but the greater
#          they are, the longer it will take to run the function.
# Time_points: The length of the interval between time points for predictions.
# Median_precision: The method to compute the median precision. Either the Mean squared
error (MSE) or
#                  the Mean absolute error (MAE).

robustness_sim <- function(n_sim, real_t_tot, n, Start_date = date("2019/12/1"),
                           m, n_pred, diff_month, V_lambda, Time_points,
                           Median_precision = c("MSE", "MAE")){

  # First Part: Generate the n_sim simulations ####
  Real_trials <- lapply(X = 1:n_sim, FUN = function(jj){
    # Define real lambda
    lambda_real <- (real_t_tot*(365.25/12))/n

    # Compute the waiting time based on the real value of lambda for the simulation
    Waiting_Time_real <- rexp(n, 1/lambda_real)
    Waiting_Time_real_cumsum <- cumsum(Waiting_Time_real)

    # Create real subject dataset
    subject_real <- data.frame(id = 1:n, arrival_date = Start_date, inter_arrival =
Waiting_Time_real,
                               cum_inter_arrival = Waiting_Time_real_cumsum)
```

```
  subject_real$arrival_date <- subject_real$arrival_date+subject_real$cum_inter_arrival

  # Trial duration in month ####
  Tot_day <- as.numeric(subject_real$arrival_date[n]-Start_date)
  correct_label <- Start_date+1:round(Tot_day)
  correct_label <- unique(paste(month(correct_label), year(correct_label)))
  t_tot_observed <- length(correct_label)

  return(list(t_tot_observed, subject_real))
})

# Get Real_trials dataset
Real_trials_dataset <- lapply(Real_trials, "[[", 2)

# Get real trial duration
Real_trials_duration <- unlist(lapply(Real_trials, "[[", 1))
print(summary(Real_trials_duration))

# Second Part: Define general summary tables for results ####
# All the remaining tables will resume information from tables in each simulation
# We will compute the mean of results
# General IC width ####
# Create base table and fill it in the loops
General_IC_width <- as.data.frame(matrix(0, ncol = 1+length(V_lambda), nrow = 5))
rownames(General_IC_width) <- c(3, 6, 9, 12, "t_tot")
colnames(General_IC_width) <- c("Time Point (in month)", paste("V = ", V_lambda))

# Create a list of m elements for all
General_IC_width_Evol_list <- rep(list(General_IC_width), (length(m)+1))

# General Median Precision ####
# Create base table and fill it in the loops
General_Med_precision <- as.data.frame(matrix(0, ncol = 1+length(V_lambda), nrow = 5))
rownames(General_Med_precision) <- c(3, 6, 9, 12, "t_tot")
colnames(General_Med_precision) <- c("Time Point (in month)", paste("V = ", V_lambda))

# Create a list of m elements for all
General_Median_precision_list <- rep(list(General_Med_precision), (length(m)+1))

# General real recruitment covered by 90% IC ####
# Create base table and fill it in the loops
General_IC_cover <- as.data.frame(matrix(0, ncol = 1+length(V_lambda), nrow = 5))
rownames(General_IC_cover) <- c(3, 6, 9, 12, "t_tot")
colnames(General_IC_cover) <- c("Time Point (in month)", paste("V = ", V_lambda))
```

```
# Create a list of m elements for all
General_IC_coverage_list <- rep(list(General_IC_cover), (length(m)+1))

# Third Part: Perform the simulation studies ####
# Store the results of each simulation
simulations <- lapply(1:n_sim, FUN = function(jj){
  print(jj)
  # Real data ####
  # Import real trial data
  subject_real <- Real_trials_dataset[[jj]]

  # Define real_t_tot
  real_t_tot <- Real_trials_duration[jj]

  # Define t_tot prior ####
  # The expected duration is the real duration minus the planned duration error
  t_tot <- real_t_tot - diff_month
  print(t_tot)

  # Define Time point for each m ####
  # They represent a sequence of values at regular intervals, which is define in the function by
  # the Time_points argument
  time_point <- lapply(X = 1:(length(m)+1), FUN = function(jj){
    set2 <- seq(Time_points, by = Time_points, length.out = 5)
    if(jj==1) set2
    else{
      # Compute the number of months between Start_date and last arrival
      Nbr_months <- Start_date+1:ceiling(subject_real$arrival_date[m[jj-1]]-Start_date)
      Nbr_months <- length(unique(paste(month(Nbr_months), year(Nbr_months))))

      if(sum((Nbr_months+set2) > real_t_tot) == 0) (Nbr_months+set2)
      else{
        # Take the month pred before real_t_tot
        lower <- (Nbr_months+set2)[which((Nbr_months+set2) < real_t_tot)]
        # Save
        c(lower, real_t_tot)
      }
    }
  })

  # IC width ####
  # Create tables and lists to stock the tables
```

```
  # IC_width_Evol_list gives the different widths of 90% IC for one m value and multiple
variance of lambda
  # at several time points
  IC_width_Evol_list <- list()
  # Create base table and fill it in the loops
  IC_width <- as.data.frame(matrix(ncol = 1+length(V_lambda), nrow =
length(time_point[[1]])))
  colnames(IC_width) <- c("Time Point (in month)", paste("V = ", V_lambda))

  # Median Precision ####
  # Median_precision_list compute either the MSE or the MAE
  # between the real recruitment number and the prediction for one m value
  # and multiple variance of lambda
  Median_precision_list <- list()
  # Create base table and fill it in the loops
  Med_precision <- as.data.frame(matrix(ncol = 1+length(V_lambda), nrow =
length(time_point[[1]])))
  colnames(Med_precision) <- c("Time Point (in month)", paste("V = ", V_lambda))

  # Prediction details ####
  # IC_details gives all the 90% IC informations and median prediction estimate
  # for one m and one variance of lambda at several time points
  IC_details <- list()
  # Create base table and fill it in the loops
  Pred_comparison <- as.data.frame(matrix(ncol = 6, nrow = length(time_point[[1]])))
  colnames(Pred_comparison) <- c("Time Point (in month)", "Real recruitment",
                         "Lower 90% IC post", "Median post", "Upper 90% IC post", "IC width")

  # Real recruitment covered by 90% IC ####
  # IC_coverage_list tells us whether or not the 90% IC contains the true recruitment numbers
for one value of m and
  # multiple variance of lambda
  IC_coverage_list <- list()
  # Create base table and fill it in the loops
  IC_cover <- as.data.frame(matrix(ncol = 1+length(V_lambda), nrow =
length(time_point[[1]])))
  colnames(IC_cover) <- c("Time Point (in month)", paste("V = ", V_lambda))

  # Expected waiting time of the study ####
  # Compute prior on lambda knowing waiting time has an exponential distribution with
lambda, the scale parameter.
  # Prior mean on lambda is measured by the expected waiting time between patient (in days)
  lambda_0 <- (t_tot*(365.25/12))/n
```

```
  # Bayesian setting, an inverse gamma distribution is considered for the parameter lambda of the exponential distribution
  # Find prior value for alpha and beta considering E(lambda) = lambda_0 and V(lambda) = constant introduced in the function
  E_lambda <- lambda_0
  cat("E(lambda) =", E_lambda)

  # Stan Model ####
  # Introduce the Stan model define above
  Analyse_Prior_R = readRDS("Analyse_Prior_R.rds")

  # Loop on V(lambda) ####
  # For each V(lambda) introduced in the function, compute the different results of interest
  for(e in 1:length(V_lambda)){
    # Compute prior predictions on the trial
    # Compute prior paramater values
    alpha_0 <- E_lambda^2/V_lambda[e]+2
    beta_0 <- E_lambda*(alpha_0-1)

    # Sample 1000 different waiting time prior prediction, with for each waiting time,
    # a new lambda from the inverse gamma distribution (in order to have IC)
    # Then with the trial start date, define subjects arrival dates and compute recruitment per month
    Prior_pred <- lapply(1:1000, FUN = function(jj){
      # For each waiting time w_i, sample a lambda from the prior distribution and use it in the exponential
      lambda_0 <- rinvgamma(n_pred, alpha_0, rate = beta_0)
      w <- rexp(n_pred, 1/lambda_0)

      # Then compute arrival date from trial start date
      d <- Start_date+cumsum(w)

      # Create a new variable that includes only month and year
      m_y <- paste(month(d), year(d))

      # Count the number of subject recruited per month
      # Problem, 1 2021 comes before 2 2020
      # Thus create a prevariable with label in correct order and work in another lapply
      # Create a variable for the maximum number of days to recruit n_pred subjects
      t_tot_1000 <- as.numeric(d[n_pred]-Start_date)

      # Return the arrival dates, the month and year and the trial length
      list(d, m_y, t_tot_1000)
    })
```

```
# Get the maximum difference in number of days
max_t_tot <- max(unlist(lapply(Prior_pred, "[[", 3)))
# To ensure the real t_tot is included in the maximum time duration
max_t_tot <- max(max_t_tot, as.numeric(subject_real$arrival_date[n]-Start_date))

# Create the correct label order
# Compute a variable with all the dates from trial start date to trial last date possible in
prediction
# Then only keep one month and year combination in correct order
correct_label <- Start_date+1:round(max_t_tot)
correct_label <- unique(paste(month(correct_label), year(correct_label)))

# Count the cumulative sum of subject recruited per month in each prediction
Prior_pred <- lapply(1:1000, FUN = function(jj){
  d <- unlist(Prior_pred[[jj]][2])
  d <- factor(d, levels = correct_label)
  d <- table(d)
  list(cumsum(d))
})

# For each month, get the 1000 cumulative sum of subject recruited in the prediction
Prior_pred <- lapply(1:length(correct_label), FUN = function(jj){
  d <- lapply(Prior_pred, "[[", 1)
  d <- unlist(unlist(lapply(d, "[[", jj)))
  # Get the median value of subjects recruited in each month and the 90% HDI
  list(hdi(d, credMass = .90)[1], median(d), hdi(d, credMass = .90)[2])
})

# Retrieve the quantities of interest from the prior predictive distribution (median and 90%
HDI)
q05_prior <- round(unlist(lapply(Prior_pred, "[[", 1)), 0)
q5_prior <- round(unlist(lapply(Prior_pred, "[[", 2)), 0)
q95_prior <- round(unlist(lapply(Prior_pred, "[[", 3)), 0)

# Count real data per month
# Count per month
real_d <- paste(month(subject_real$arrival_date), year(subject_real$arrival_date))
real_d <- factor(real_d, levels = correct_label)
real_d <- as.numeric(table(real_d))

# IC_details
# Create a list inside the variance
IC_details_V <- list()
```

```
    # Update table
    Pred_comparison[,1] <- time_point[[1]]
    Pred_comparison[,2] <- cumsum(real_d)[time_point[[1]]]
    Pred_comparison[,3] <- q05_prior[time_point[[1]]]
    Pred_comparison[,4] <- q5_prior[time_point[[1]]]
    Pred_comparison[,5] <- q95_prior[time_point[[1]]]
    Pred_comparison[,6] <- Pred_comparison[,5] - Pred_comparison[,3]

    IC_details_V[[1]] <- Pred_comparison

    # IC_width_Evol_list
    # Store the different results in their respective tables
    # if first column to be fulfill, just assigns IC_width
    if(e == 1){
      # IC_width
      IC_width[,1] <- time_point[[1]]
      IC_width[,1+e] <- Pred_comparison[,6]
      IC_width_Evol_list[[1]] <- IC_width

      # Median Precision
      Med_precision[,1] <- time_point[[1]]

      # Compute the Median precision depending on the type chosen
      if(Median_precision == "MSE") Med_precision[,1+e] <- (Pred_comparison[,2] -
Pred_comparison[,4])^2
      else if(Median_precision == "MAE") Med_precision[,1+e] <- abs(Pred_comparison[,2] -
Pred_comparison[,4])
      else return(print("No Median precision selected, error"))

      Median_precision_list[[1]] <- Med_precision

      # 90% IC Coverage
      IC_cover[,1] <- time_point[[1]]
      # if the true recuitment value is covered by 90% IC, value is 1, otherwise 0
      # index gives time points where true value is included
      index <- which(Pred_comparison[,2] >= Pred_comparison[,3] & Pred_comparison[,2] <=
Pred_comparison[,5])
      # if no time points, all values are 0
      IC_cover[,1+e] <- 0
      # if some time points, put their values at 1
      if(length(index) != 0) IC_cover[index,1+e] <- 1

      IC_coverage_list[[1]] <- IC_cover
```

```
    } # end if(e == 1)
    # else fulfill the right IC_width_Evol_list
    else{
      # IC_width
      #IC_width_Evol_list[[1]][,1] <- time_point[[1]]
      IC_width_Evol_list[[1]][,1+e] <- Pred_comparison[,6]

      # Median Precision
      # Compute the Median precision depending on the type chosen
      if(Median_precision == "MSE") Median_precision_list[[1]][,1+e] <-
(Pred_comparison[,2] - Pred_comparison[,4])^2
      else if(Median_precision == "MAE") Median_precision_list[[1]][,1+e] <-
abs(Pred_comparison[,2] - Pred_comparison[,4])
      else return(print("No Median precision selected, error"))

      # 90% IC Coverage
      #IC_coverage_list[[1]][,1] <- time_point[[1]]
      # index gives time points where true value is included
      index <- which(Pred_comparison[,2] >= Pred_comparison[,3] & Pred_comparison[,2] <=
Pred_comparison[,5])
      # if no time points, all values are 0
      IC_coverage_list[[1]][,1+e] <- 0

      # if some time points, put their values at 1
      if(length(index) != 0) IC_coverage_list[[1]][index,1+e] <- 1
    } #end else of if(e == 1)

    # Then consider the predictions when m subjects are in the trial
    # Model 1 : Model with informative prior
    # Fit the model depending on the information we have on real data to adjust prediction
based on prior
    # Inter-Arrival Time Model ==> Time to recruit a new patient
    # Here we will consider n data at a time, we will use a exponential to predict the arrival of
n-m patients
    # within a certain period

    for(i in 1:length(m)){
      # Model 1 Estimation
      # Define the number of subjects in the study
      m_test <- m[i]

      # Define model parameters
      # Waiting Time
```

```
y <- subject_real$inter_arrival[1:m_test]
# Size of the dataset used
N_y <- length(y)
# Prior on alpha and beta (already defined above)

# Create list for Stanfitting
arrlist = list(y=y, N=N_y, alpha_p=alpha_0, beta_p=beta_0)

# Fit the model
Analyse_Prior_Fit = sampling(object = Analyse_Prior_R, data = arrlist, chains = 4,
                    iter = 2000, warmup = 1000, thin = 4)

# Extract chains
Analyse_Prior_Para1 = extract(Analyse_Prior_Fit)
print(summary(Analyse_Prior_Para1$lambda))

# Compute Prediction
# Sample 1000 different waiting time posterior prediction, with for each waiting time,
# a new lambda from the posterior lambda distribution (in order to have IC)
# Then with the trial start date, define subjects arrival dates and compute recruitment per
month
Post_pred <- lapply(X = 1:1000, FUN = function(jj){
  # Sample one lambda from posterior
  lambda_post <- Analyse_Prior_Para1$lambda[jj]
  w <- rexp(n_pred, 1/lambda_post)

  # Then compute arrival date from trial start date
  d <- c(subject_real$arrival_date[1:m_test],
subject_real$arrival_date[m_test]+cumsum(w))

  # Create a new variable that includes only month and year
  m_y <- paste(month(d), year(d))

  # Create a variable for the maximum number of days to recruit n_pred subjects
  t_tot_1000 <- as.numeric(d[n_pred]-Start_date)

  # Return the arrival dates, the month and year and the trial length
  list(d, m_y, t_tot_1000)
})

# Get the maximum difference in number of days
max_t_tot <- max(unlist(lapply(Post_pred, "[[", 3)))
# To ensure the real t_tot is included in the maximum time duration
max_t_tot <- max(max_t_tot, as.numeric(subject_real$arrival_date[n]-Start_date))
```

```
        # Create the correct label order
        # Compute a variable with all the dates from trial start date to trial last date possible in
prediction
        # Then only keep one month and year combination in correct order
        correct_label <- Start_date+1:round(max_t_tot)
        correct_label <- unique(paste(month(correct_label), year(correct_label)))

        # Count the cumulative sum of subject recruited per month in each prediction
        Post_pred <- lapply(1:1000, FUN = function(jj){
          d <- unlist(Post_pred[[jj]][2])
          d <- factor(d, levels = correct_label)
          d <- table(d)
          list(cumsum(d))
        })

        # For each month, get the 1000 cumulative sum of subject recruited in the prediction
        Post_pred <- lapply(1:length(correct_label), FUN = function(jj){
          d <- lapply(Post_pred, "[[", 1)
          d <- unlist(unlist(lapply(d, "[[", jj)))
          # Get the median value of subjects recruited in each month and the 90% HDI
          list(hdi(d, credMass = .90)[1], median(d), hdi(d, credMass = .90)[2])
        })

        # Retrieve the quantities of interest from the posterior predictive distribution (median and
90% HDI)
        q05_post <- unlist(lapply(Post_pred, "[[", 1))
        q5_post <- round(unlist(lapply(Post_pred, "[[", 2)), 0)
        q95_post <- unlist(lapply(Post_pred, "[[", 3))

        # IC_details
        # Update table
        Pred_comparison[,1] <- time_point[[1+i]]
        Pred_comparison[,2] <- cumsum(real_d)[time_point[[1+i]]]
        Pred_comparison[,3] <- q05_post[time_point[[1+i]]]
        Pred_comparison[,4] <- q5_post[time_point[[1+i]]]
        Pred_comparison[,5] <- q95_post[time_point[[1+i]]]
        Pred_comparison[,6] <- Pred_comparison[,5] - Pred_comparison[,3]

        IC_details_V[[i+1]] <- Pred_comparison

        # IC_width_Evol_list
        # Store the different results in their respective tables
        # if first column to be fulfill, just assigns IC_width
```

```
      if(e == 1){
        # IC_width
        IC_width[,1] <- time_point[[1+i]]
        IC_width[,1+e] <- Pred_comparison[,6]
        IC_width_Evol_list[[1+i]] <- IC_width

        # Median Precision
        Med_precision[,1] <- time_point[[1+i]]

        # Compute the Median precision depending on the type chosen
        if(Median_precision == "MSE") Med_precision[,1+e] <- (Pred_comparison[,2] -
Pred_comparison[,4])^2
        else if(Median_precision == "MAE") Med_precision[,1+e] <- abs(Pred_comparison[,2]
- Pred_comparison[,4])
        else return(print("No Median precision selected, error"))

        Median_precision_list[[1+i]] <- Med_precision

        # 90% IC Coverage
        IC_cover[,1] <- time_point[[1+i]]
        # if the true recuitment value is covered by 90% IC, value is 1, otherwise 0
        # index gives time points where true value is included
        index <- which(Pred_comparison[,2] >= Pred_comparison[,3] & Pred_comparison[,2]
<= Pred_comparison[,5])
        # if no time points, all values are 0
        IC_cover[,1+e] <- 0
        # if some time points, put their values at 1
        if(length(index) != 0) IC_cover[index,1+e] <- 1

        IC_coverage_list[[1+i]] <- IC_cover
      }
      # else fulfill the right IC_width_Evol_list
      else{
        # IC_width
        #IC_width_Evol_list[[1+i]][,1] <- time_point[[1+i]]
        IC_width_Evol_list[[1+i]][,1+e] <- Pred_comparison[,6]

        # Median Precision
        # Median Precision
        # Compute the Median precision depending on the type chosen
        if(Median_precision == "MSE") Median_precision_list[[1+i]][,1+e] <-
(Pred_comparison[,2] - Pred_comparison[,4])^2
        else if(Median_precision == "MAE") Median_precision_list[[1+i]][,1+e] <-
abs(Pred_comparison[,2] - Pred_comparison[,4])
```

```
    else return(print("No Median precision selected, error"))

    # 90% IC Coverage
    # index gives time points where true value is included
    index <- which(Pred_comparison[,2] >= Pred_comparison[,3] & Pred_comparison[,2]
<= Pred_comparison[,5])
    # if no time points, all values are 0
    IC_coverage_list[[1+i]][,1+e] <- 0

    # if some time points, put their values at 1
    if(length(index) != 0) IC_coverage_list[[1+i]][index,1+e] <- 1
   }

  } # fin boucle m

  # Update list IC_details
  IC_details[[e]] <- IC_details_V

 } #end V(lambda) loop

 # Update General Tables ####
 # General tables with a table by m value
 for(i in 1:(length(m)+1)){
  # General IC width
  General_IC_width_Evol_list[[i]]        <<-        General_IC_width_Evol_list[[i]]        +
IC_width_Evol_list[[i]]

  # General median Precision
  General_Median_precision_list[[i]]      <<-      General_Median_precision_list[[i]]      +
Median_precision_list[[i]]

  # General real recruitment covered by 90% IC
  General_IC_coverage_list[[i]] <<- General_IC_coverage_list[[i]] + IC_coverage_list[[i]]

  if(jj == n_sim){
   # General IC width
   General_IC_width_Evol_list[[i]] <<- General_IC_width_Evol_list[[i]]/n_sim
   #General_IC_width_Evol_list[[i]][,1] <<- c(3, 6, 9, 12, "t_tot")

   # General median Precision
   General_Median_precision_list[[i]][] <<- General_Median_precision_list[[i]]/n_sim
   #General_Median_precision_list[[i]][,1] <<- c(3, 6, 9, 12, "t_tot")

   # General real recruitment covered by 90% IC
```

```
      General_IC_coverage_list[[i]][] <<- General_IC_coverage_list[[i]]/n_sim
      #General_IC_coverage_list[[i]][,1] <<- c(3, 6, 9, 12, "t_tot")
    }
  }

  # Return list at simulation level ####
  list(IC_details, IC_width_Evol_list, Median_precision_list, IC_coverage_list)
 }) # end lapply

 # Return all the all the results from simulation and all the general tables
 return(list(simulations, General_IC_width_Evol_list, General_Median_precision_list,
General_IC_coverage_list))

} # end function robustness_sim
```

Annexe 2. Simulations studies graphics and tables

For each setting, we present the graphics that were not displayed as well as the tables summarizing all the information for the prediction accuracy of the three scenarios. Two results are always displayed:

- The prediction accuracy based on the median number of subjects recruited per month. One graph is displayed per m value. It shows the MSE for the different priors at various time points from the month where patient m was recruited. m=0 corresponds to the prior.
- The number of times the real recruitment value is included in the 90% credibility intervals. One graph is displayed per m value. It shows the coverage rates for the different priors at various time points from the month where patient m was recruited. m=0 corresponds to the prior

6.1.2 Annexe 2.1 First Setting

Scenario 1: $T_{expected}$ at 12 months

	Time Point (in month)	Median Precision at V(λ) = 0.01	0.05	0.1	0.5	1	5	Correct Coverage at V(λ) = 0.01	0.05	0.1	0.5	1	5
Prior	3	69.50	69.64	69.61	70.14	71.25	79.11	0.71	0.71	0.71	0.73	0.76	0.87
	6	237.61	237.81	237.50	239.39	241.21	259.89	0.45	0.46	0.46	0.49	0.52	0.71
	9	504.28	506.14	505.81	507.67	511.21	540.44	0.26	0.26	0.26	0.28	0.31	0.53
	12	869.83	871.05	871.73	875.23	879.32	918.80	0.14	0.14	0.14	0.15	0.17	0.34
	15	1332.29	1334.34	1332.85	1338.40	1342.03	1394.94	0.06	0.07	0.06	0.08	0.08	0.18
m = 10	3	92.28	87.88	84.65	80.82	87.00	113.93	0.67	0.73	0.78	0.90	0.92	0.92
	6	273.11	259.01	246.68	231.06	254.30	346.96	0.45	0.55	0.65	0.88	0.91	0.92
	9	560.15	529.20	503.20	470.69	520.88	725.94	0.26	0.41	0.56	0.85	0.91	0.91
	12	939.66	888.06	842.41	788.91	869.63	1227.40	0.15	0.29	0.46	0.86	0.90	0.92
	15	1412.33	1329.14	1257.20	1170.15	1296.11	1843.84	0.08	0.20	0.39	0.86	0.91	0.92
m = 20	3	90.49	81.14	73.92	62.18	62.68	69.04	0.67	0.74	0.82	0.90	0.92	0.91
	6	269.58	238.04	212.57	169.84	172.50	192.18	0.45	0.58	0.69	0.89	0.91	0.91
	9	538.06	469.94	416.94	322.92	327.52	370.26	0.28	0.47	0.62	0.87	0.91	0.90
	12	908.17	791.08	696.34	530.95	536.36	607.82	0.16	0.34	0.54	0.87	0.91	0.92
	15	1383.59	1197.56	1053.44	791.93	798.93	903.51	0.09	0.26	0.48	0.86	0.91	0.91
m = 30	3	86.49	73.44	64.41	50.46	49.75	51.43	0.71	0.78	0.84	0.92	0.91	0.91
	6	261.75	216.67	184.73	134.20	132.19	137.02	0.46	0.63	0.74	0.90	0.89	0.90
	9	530.95	433.05	364.73	250.26	243.94	251.69	0.28	0.50	0.66	0.88	0.90	0.91
	12	888.38	717.36	597.07	396.83	384.77	396.13	0.17	0.39	0.60	0.89	0.90	0.92
	15	1332.18	1069.53	885.73	583.44	564.28	581.64	0.10	0.32	0.55	0.89	0.90	0.91
m = 40	3	85.80	69.17	58.62	44.28	43.45	44.31	0.69	0.80	0.84	0.92	0.92	0.92
	6	255.28	198.01	161.91	110.69	107.14	108.90	0.48	0.67	0.77	0.90	0.91	0.90
	9	513.20	392.12	313.91	201.68	192.94	194.80	0.28	0.52	0.70	0.90	0.91	0.91
	12	867.23	657.23	518.88	323.12	307.55	309.46	0.17	0.44	0.64	0.90	0.91	0.92
	15	1297.03	974.15	768.16	474.47	451.85	459.03	0.11	0.37	0.60	0.89	0.90	0.90
m = 50	3	87.59	68.25	57.22	43.17	42.20	42.72	0.69	0.79	0.85	0.90	0.90	0.89
	6	253.99	187.79	149.32	99.52	95.72	96.41	0.48	0.68	0.79	0.90	0.91	0.91
	9	511.42	369.91	287.27	178.89	169.78	169.49	0.31	0.55	0.71	0.89	0.90	0.90
	12	853.35	610.03	469.88	285.92	271.70	271.20	0.19	0.47	0.66	0.90	0.90	0.89
	15	1277.76	903.57	687.33	404.65	385.06	384.31	0.12	0.40	0.62	0.89	0.89	0.90
m = 100	3	77.57	51.44	41.65	32.61	32.22	31.47	0.72	0.85	0.89	0.91	0.91	0.91
	6	227.29	138.25	102.85	72.67	71.57	70.81	0.54	0.76	0.84	0.91	0.90	0.90
	9	458.46	266.49	189.32	121.65	117.57	116.91	0.34	0.68	0.80	0.91	0.91	0.91
	12	761.81	430.38	297.57	180.45	173.97	171.22	0.23	0.61	0.79	0.92	0.92	0.91
	15	1155.13	644.39	441.78	260.18	249.34	246.17	0.14	0.55	0.74	0.90	0.91	0.90

Scenario 2: $T_{expected}$ at 6 months

	Time Point (in month)	Median Precision at V(λ) = 0.01	0.05	0.1	0.5	1	5	Correct Coverage at V(λ) = 0.01	0.05	0.1	0.5	1	5
Prior	3	27.93	27.98	27.97	28.09	28.35	30.64	0.90	0.91	0.91	0.91	0.92	0.96
	6	71.08	71.46	71.54	71.96	72.53	77.82	0.85	0.85	0.86	0.87	0.88	0.94
	9	129.37	128.72	129.27	130.21	130.98	140.36	0.81	0.82	0.82	0.83	0.84	0.92
	12	204.23	203.99	204.51	206.06	206.74	219.92	0.76	0.76	0.76	0.78	0.79	0.90
	15	290.60	289.85	292.34	293.60	293.60	311.09	0.69	0.70	0.70	0.72	0.75	0.87
m = 10	3	36.27	36.51	37.19	43.88	53.72	90.42	0.88	0.89	0.91	0.94	0.95	0.92
	6	81.85	82.39	82.69	105.47	137.67	266.06	0.85	0.87	0.91	0.95	0.96	0.94
	9	147.47	146.93	150.18	198.67	269.34	548.68	0.81	0.86	0.90	0.96	0.96	0.93
	12	225.11	224.84	229.22	312.43	432.58	918.15	0.75	0.83	0.89	0.96	0.96	0.94
	15	316.03	316.27	322.54	444.55	628.61	1367.60	0.72	0.81	0.88	0.96	0.97	0.93
m = 20	3	35.90	35.47	35.60	41.04	47.25	62.44	0.89	0.90	0.91	0.93	0.93	0.91
	6	82.77	81.78	81.60	98.71	119.61	169.24	0.85	0.89	0.91	0.94	0.93	0.91
	9	142.39	139.47	138.79	173.14	217.95	321.98	0.82	0.87	0.90	0.94	0.94	0.91
	12	219.44	213.46	211.72	268.58	344.47	523.82	0.75	0.84	0.89	0.94	0.94	0.92
	15	312.50	303.15	300.56	386.47	499.47	779.22	0.74	0.80	0.88	0.94	0.94	0.92
m = 30	3	34.99	34.52	34.17	37.97	41.43	49.26	0.90	0.90	0.92	0.92	0.93	0.92
	6	82.59	80.31	78.99	91.45	104.10	128.58	0.85	0.88	0.90	0.92	0.91	0.90
	9	143.69	136.40	133.49	157.94	182.69	232.41	0.82	0.86	0.89	0.94	0.93	0.92
	12	217.05	206.11	198.85	239.05	279.44	363.12	0.77	0.85	0.89	0.93	0.93	0.91
	15	303.92	286.16	276.19	339.11	404.70	534.30	0.73	0.83	0.89	0.93	0.92	0.91
m = 40	3	34.45	33.25	32.94	35.59	38.29	42.71	0.90	0.91	0.93	0.93	0.93	0.92
	6	80.30	75.89	73.60	81.78	89.06	102.82	0.85	0.88	0.90	0.92	0.92	0.91
	9	136.94	127.09	122.51	137.87	154.12	182.76	0.81	0.87	0.91	0.93	0.92	0.91
	12	212.80	194.65	187.02	212.14	239.79	288.10	0.77	0.86	0.90	0.93	0.93	0.91
	15	297.90	272.06	261.10	303.91	349.92	425.70	0.73	0.84	0.89	0.94	0.92	0.90
m = 50	3	36.76	35.42	34.58	36.78	38.80	41.25	0.88	0.90	0.92	0.91	0.90	0.90
	6	80.42	75.03	72.33	77.90	83.55	92.37	0.85	0.89	0.90	0.91	0.92	0.91
	9	141.16	128.67	122.47	131.97	144.35	161.47	0.81	0.88	0.91	0.92	0.92	0.91
	12	214.79	194.05	185.01	203.98	226.26	257.84	0.77	0.85	0.90	0.92	0.91	0.90
	15	299.70	266.78	251.58	281.91	313.70	364.10	0.73	0.82	0.88	0.92	0.92	0.90
m = 100	3	34.05	31.39	30.16	30.46	30.82	31.88	0.89	0.91	0.92	0.91	0.91	0.91
	6	76.93	68.09	64.61	65.41	67.52	70.12	0.85	0.89	0.91	0.91	0.91	0.90
	9	134.27	113.19	105.46	105.19	109.02	113.92	0.82	0.88	0.91	0.92	0.90	0.92
	12	201.23	165.40	151.25	153.08	159.13	168.04	0.80	0.87	0.91	0.93	0.91	0.91
	15	291.95	236.05	214.82	218.09	226.49	240.34	0.75	0.85	0.89	0.92	0.91	0.90

Scenario 3: $T_{expected}$ at 3 months

	Time Point (in month)	Median Precision at V(λ) = 0.01	0.05	0.1	0.5	1	5	Correct Coverage at V(λ) = 0.01	0.05	0.1	0.5	1	5
Prior	3	21.06	21.00	20.87	21.07	21.25	22.30	0.93	0.93	0.93	0.94	0.95	0.98
	6	43.48	43.74	44.02	43.58	43.44	45.80	0.93	0.92	0.92	0.93	0.94	0.97
	9	65.95	65.99	65.64	66.36	66.51	69.97	0.92	0.92	0.93	0.93	0.94	0.97
	12	92.83	92.37	92.26	92.84	93.48	98.60	0.92	0.92	0.92	0.92	0.93	0.97
	15	114.15	114.56	114.55	114.91	115.50	122.28	0.92	0.93	0.93	0.94	0.94	0.97
m = 10	3	27.10	27.39	28.07	34.32	42.50	79.11	0.92	0.93	0.93	0.95	0.94	0.93
	6	49.41	50.86	51.93	72.47	100.01	227.25	0.93	0.94	0.95	0.97	0.98	0.95
	9	76.75	79.17	82.86	126.86	187.28	465.46	0.92	0.94	0.94	0.98	0.97	0.94
	12	101.01	105.23	111.67	186.59	290.55	773.37	0.92	0.94	0.95	0.98	0.98	0.94
	15	125.88	131.45	141.22	253.27	411.45	1145.81	0.92	0.94	0.96	0.98	0.98	0.95
m = 20	3	27.06	27.25	28.00	34.37	41.40	59.02	0.92	0.92	0.93	0.94	0.93	0.92
	6	50.86	52.58	54.62	76.06	98.73	157.67	0.92	0.93	0.94	0.95	0.94	0.92
	9	75.48	77.18	81.30	125.99	173.68	297.21	0.92	0.94	0.95	0.96	0.94	0.91
	12	98.90	102.93	110.09	187.28	266.85	479.76	0.92	0.95	0.95	0.96	0.96	0.92
	15	125.11	130.85	141.52	259.01	380.03	707.61	0.92	0.95	0.96	0.97	0.96	0.92
m = 30	3	26.43	26.83	27.44	33.63	38.36	47.34	0.91	0.93	0.93	0.92	0.93	0.92
	6	52.64	53.94	56.06	76.30	92.27	122.00	0.92	0.92	0.93	0.92	0.92	0.91
	9	74.88	77.92	82.10	123.31	156.15	220.44	0.92	0.93	0.94	0.94	0.94	0.92
	12	99.22	102.81	109.48	178.48	233.57	342.77	0.92	0.94	0.95	0.96	0.94	0.92
	15	123.31	130.13	140.03	247.32	332.72	501.74	0.92	0.94	0.96	0.95	0.94	0.92
m = 40	3	25.79	26.32	26.94	32.16	35.80	41.63	0.92	0.93	0.94	0.94	0.93	0.92
	6	50.08	51.29	52.93	69.65	81.73	100.13	0.92	0.93	0.94	0.93	0.92	0.91
	9	69.70	72.11	75.51	112.07	136.97	176.65	0.94	0.95	0.96	0.94	0.93	0.92
	12	95.02	98.51	104.83	167.51	208.85	277.68	0.93	0.95	0.96	0.95	0.93	0.92
	15	120.42	126.13	138.66	236.50	302.66	410.50	0.92	0.95	0.96	0.95	0.94	0.92
m = 50	3	27.95	28.34	29.19	34.07	36.81	40.80	0.91	0.92	0.92	0.92	0.91	0.90
	6	49.65	50.77	53.15	68.85	77.86	90.69	0.92	0.93	0.93	0.93	0.92	0.90
	9	73.46	76.15	81.12	112.37	130.81	157.85	0.92	0.93	0.94	0.93	0.92	0.91
	12	98.88	103.95	112.89	169.98	202.70	252.03	0.94	0.95	0.95	0.93	0.92	0.90
	15	123.47	129.54	143.50	229.71	279.51	355.62	0.92	0.94	0.95	0.94	0.93	0.91
m = 100	3	25.56	26.10	26.62	28.99	30.28	31.45	0.92	0.92	0.91	0.92	0.91	0.90
	6	49.11	50.28	52.79	61.96	65.39	69.28	0.91	0.93	0.93	0.92	0.91	0.90
	9	71.32	73.73	78.65	97.16	104.78	113.32	0.92	0.94	0.94	0.92	0.92	0.91
	12	94.43	97.79	106.11	138.68	151.55	165.58	0.93	0.94	0.95	0.93	0.92	0.92
	15	124.73	130.76	143.77	195.28	215.62	237.26	0.91	0.93	0.94	0.92	0.91	0.91

Scenario 4: $T_{expected}$ at 0 months

	Time Point (in month)	Median Precision at V(λ) =						Correct Coverage at V(λ) =					
		0.01	0.05	0.1	0.5	1	5	0.01	0.05	0.1	0.5	1	5
Prior	3	19.11	19.32	19.20	19.35	19.24	19.43	0.92	0.92	0.92	0.93	0.93	0.97
	6	36.75	37.03	36.93	36.81	36.84	36.83	0.92	0.92	0.92	0.93	0.94	0.97
	9	51.42	51.56	51.71	51.38	51.36	51.60	0.94	0.93	0.93	0.95	0.95	0.97
	12	66.62	67.08	66.94	66.71	66.78	67.07	0.93	0.94	0.94	0.94	0.94	0.97
	15	71.66	71.19	71.93	71.52	71.51	71.44	0.95	0.95	0.95	0.95	0.96	0.98
m = 10	3	24.75	25.18	25.55	29.51	35.98	69.83	0.91	0.91	0.92	0.95	0.95	0.93
	6	42.22	42.77	43.82	57.19	77.76	193.71	0.93	0.94	0.94	0.98	0.97	0.96
	9	60.11	61.18	63.21	92.74	138.00	389.84	0.93	0.94	0.96	0.97	0.98	0.94
	12	70.80	73.29	77.18	127.00	204.92	642.32	0.94	0.95	0.97	0.98	0.98	0.95
	15	77.78	80.86	86.22	161.10	278.09	945.45	0.95	0.97	0.98	0.99	0.98	0.94
m = 20	3	24.72	25.15	25.60	30.90	36.94	55.45	0.92	0.92	0.92	0.93	0.93	0.92
	6	43.53	44.82	46.40	63.59	83.63	145.49	0.91	0.92	0.93	0.94	0.94	0.92
	9	59.65	61.75	64.97	101.08	140.92	272.33	0.92	0.94	0.95	0.96	0.95	0.91
	12	69.63	73.01	78.42	139.98	209.18	433.57	0.94	0.96	0.96	0.97	0.96	0.93
	15	76.31	81.58	90.68	185.32	292.30	638.73	0.95	0.97	0.98	0.97	0.96	0.92
m = 30	3	24.90	25.21	25.70	31.09	35.17	45.46	0.91	0.91	0.92	0.92	0.92	0.92
	6	46.84	47.51	49.73	67.42	82.35	116.79	0.92	0.92	0.93	0.93	0.92	0.91
	9	59.33	61.86	66.38	102.64	134.35	207.47	0.92	0.93	0.94	0.95	0.94	0.92
	12	69.60	74.14	81.02	141.66	196.34	322.38	0.93	0.95	0.96	0.97	0.95	0.92
	15	79.52	86.82	97.67	193.08	276.46	469.91	0.95	0.96	0.97	0.96	0.94	0.91
m = 40	3	24.11	24.63	25.22	30.25	33.71	40.78	0.92	0.92	0.92	0.93	0.93	0.91
	6	43.83	45.23	46.94	62.83	74.83	97.07	0.92	0.93	0.93	0.93	0.93	0.91
	9	53.78	57.12	61.26	95.92	120.78	169.68	0.94	0.95	0.96	0.95	0.94	0.92
	12	64.99	70.62	78.23	138.87	181.62	265.89	0.95	0.96	0.96	0.96	0.94	0.92
	15	77.61	86.71	98.52	192.64	260.22	391.24	0.96	0.97	0.97	0.95	0.94	0.91
m = 50	3	26.03	26.65	27.34	32.26	35.49	40.22	0.91	0.91	0.91	0.92	0.90	0.91
	6	42.51	44.20	46.60	61.92	72.34	88.43	0.93	0.92	0.93	0.93	0.92	0.91
	9	57.07	60.31	65.19	97.66	119.08	153.40	0.93	0.94	0.94	0.92	0.92	0.91
	12	69.95	77.10	86.45	145.44	182.54	242.77	0.94	0.95	0.96	0.94	0.92	0.91
	15	80.34	90.36	104.52	192.59	249.93	341.02	0.95	0.96	0.96	0.95	0.94	0.91
m = 100	3	23.42	24.31	25.14	28.55	29.86	31.34	0.92	0.92	0.91	0.91	0.90	0.90
	6	41.50	44.59	47.28	59.05	63.93	68.69	0.92	0.92	0.92	0.90	0.91	0.89
	9	54.87	60.36	66.82	91.25	101.00	111.81	0.94	0.94	0.94	0.92	0.92	0.92
	12	65.30	75.19	85.70	127.62	144.14	163.12	0.94	0.95	0.94	0.93	0.92	0.91
	15	78.13	94.13	111.59	177.41	203.19	233.80	0.95	0.95	0.94	0.92	0.92	0.91

6.1.3 Annexe 2.2 Second Setting

Scenario 1: $T_{expected}$ at 12 months

	Time Point (in month)	Median Precision at V(λ) = 0.0005	0.001	0.005	0.01	0.05	0.1	Correct Coverage at V(λ) = 0.0005	0.001	0.005	0.01	0.05	0.1
Prior	2	5082.49	5084.85	5086.73	5086.93	5126.29	5186.25	0.00	0.00	0.00	0.00	0.00	0.00
	4	19694.49	19691.47	19706.30	19710.27	19784.31	19913.93	0.00	0.00	0.00	0.00	0.00	0.00
	6	44195.22	44191.39	44200.71	44224.49	44345.40	44532.05	0.00	0.00	0.00	0.00	0.00	0.00
	8	78392.58	78383.15	78419.55	78419.66	78610.19	78863.75	0.00	0.00	0.00	0.00	0.00	0.00
	10	122397.30	122394.90	122418.80	122422.50	122661.90	122971.30	0.00	0.00	0.00	0.00	0.00	0.00
m = 15	2	6298.25	5601.89	2970.74	1916.97	793.03	673.22	0.00	0.00	0.04	0.26	0.81	0.86
	4	20850.35	18479.00	9599.28	6100.44	2397.80	2014.20	0.00	0.00	0.01	0.19	0.80	0.86
	6	43805.35	38770.21	19972.80	12583.05	4829.47	4025.11	0.00	0.00	0.00	0.16	0.81	0.87
	8	75910.28	67147.03	34459.82	21629.46	8211.27	6829.45	0.00	0.00	0.00	0.14	0.80	0.87
	10	115958.00	102542.60	52495.83	32898.92	12437.08	10300.29	0.00	0.00	0.00	0.13	0.80	0.87
m = 30	2	6702.26	5362.50	1850.69	984.14	339.87	287.60	0.00	0.00	0.13	0.45	0.85	0.89
	4	20339.18	16238.58	5572.24	2934.34	988.47	824.32	0.00	0.00	0.05	0.37	0.85	0.88
	6	41352.85	33011.07	11281.37	5905.45	1944.73	1614.60	0.00	0.00	0.02	0.32	0.86	0.88
	8	69985.22	55863.42	19119.14	9997.25	3285.49	2720.78	0.00	0.00	0.02	0.32	0.85	0.89
	10	105921.00	84579.52	28954.92	15163.28	5000.95	4144.31	0.00	0.00	0.02	0.29	0.85	0.88
m = 45	2	4999.63	3690.91	1026.26	536.58	233.07	210.84	0.00	0.00	0.28	0.61	0.88	0.88
	4	16416.02	12090.81	3278.83	1659.35	650.33	578.83	0.00	0.00	0.15	0.53	0.86	0.88
	6	34345.56	25271.18	6761.88	3367.80	1266.43	1118.32	0.00	0.00	0.11	0.49	0.86	0.88
	8	58832.65	43266.91	11509.96	5688.31	2083.07	1828.70	0.00	0.00	0.07	0.46	0.85	0.88
	10	89966.46	66115.23	17547.70	8654.68	3139.35	2749.36	0.00	0.00	0.07	0.45	0.85	0.87
m = 60	2	4897.37	3369.53	776.89	391.38	174.67	159.21	0.00	0.00	0.38	0.70	0.89	0.88
	4	15320.51	10497.94	2341.00	1131.31	457.08	413.93	0.00	0.00	0.24	0.63	0.88	0.89
	6	31883.43	21829.54	4795.56	2276.85	874.21	784.59	0.00	0.00	0.19	0.59	0.87	0.89
	8	54082.29	36989.11	8073.55	3798.09	1432.38	1275.30	0.00	0.00	0.15	0.56	0.87	0.88
	10	82253.53	56254.90	12266.22	5769.61	2162.93	1932.77	0.00	0.00	0.14	0.53	0.86	0.88
m = 75	2	4295.46	2765.92	544.40	273.65	140.33	133.72	0.00	0.00	0.48	0.76	0.88	0.89
	4	13596.39	8743.50	1666.07	792.16	353.24	328.84	0.00	0.00	0.34	0.70	0.89	0.90
	6	28266.26	18159.23	3413.18	1586.57	664.78	613.91	0.00	0.00	0.26	0.66	0.89	0.90
	8	48058.04	30871.69	5757.10	2648.35	1074.78	986.41	0.00	0.00	0.22	0.64	0.87	0.89
	10	73529.05	47263.99	8830.92	4049.34	1612.89	1473.93	0.00	0.00	0.20	0.62	0.88	0.88
m = 150	2	2756.10	1460.83	231.42	135.63	93.82	91.67	0.00	0.04	0.73	0.85	0.91	0.91
	4	8651.60	4543.92	649.57	344.59	214.36	208.74	0.00	0.00	0.62	0.83	0.89	0.90
	6	17950.84	9404.92	1297.49	656.91	380.22	365.56	0.00	0.00	0.55	0.80	0.89	0.90
	8	30527.49	16001.33	2177.29	1081.97	597.28	571.62	0.00	0.00	0.49	0.79	0.88	0.88
	10	46081.24	24111.52	3228.29	1574.09	850.08	812.54	0.00	0.00	0.45	0.76	0.87	0.88

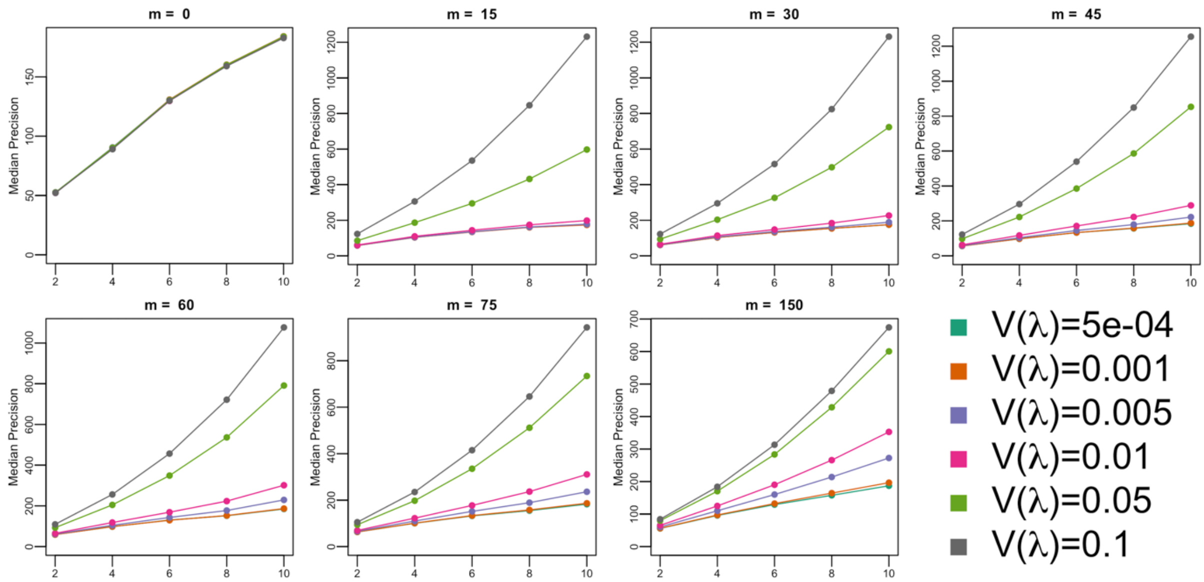
Scenario 2: $T_{expected}$ at 6 months

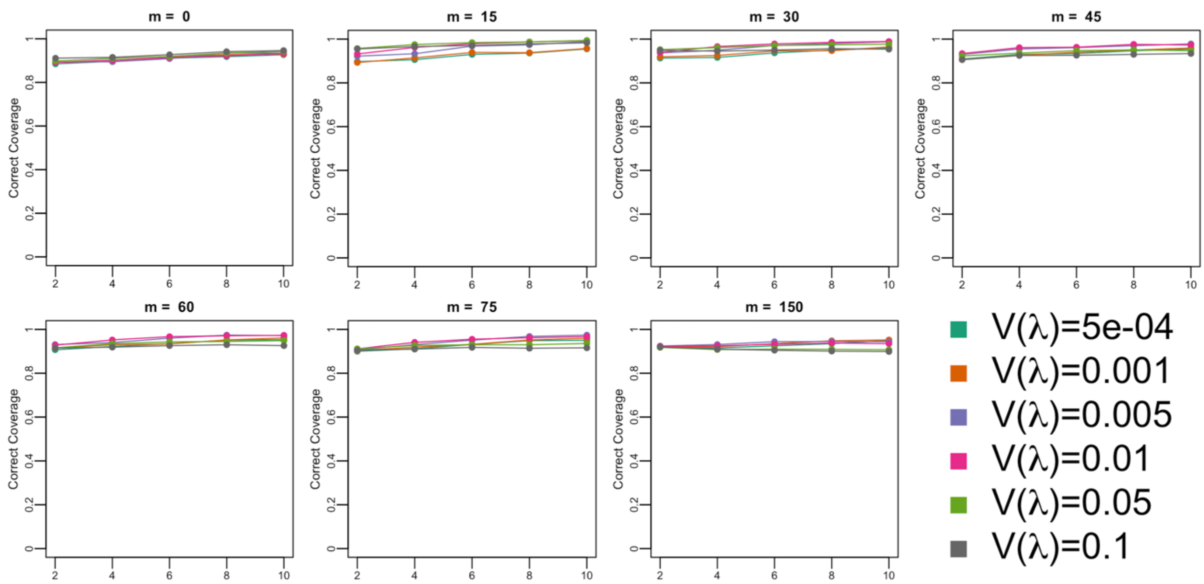
	Time Point (in month)	**Median Precision at V(λ) =**						**Correct Coverage at V(λ) =**					
		0.0005	0.001	0.005	0.01	0.05	0.1	0.0005	0.001	0.005	0.01	0.05	0.1
Prior	2	430.55	430.33	430.24	431.34	435.34	437.52	0.26	0.26	0.26	0.26	0.29	0.32
	4	1588.55	1587.91	1588.91	1589.89	1596.47	1606.22	0.04	0.04	0.03	0.04	0.05	0.06
	6	3482.74	3481.26	3486.80	3487.21	3497.45	3509.87	0.00	0.00	0.00	0.00	0.00	0.01
	8	6095.97	6099.48	6102.43	6107.37	6121.06	6137.84	0.00	0.00	0.00	0.00	0.00	0.00
	10	9449.53	9460.16	9451.35	9458.44	9477.39	9501.83	0.00	0.00	0.00	0.00	0.00	0.00
m = 15	2	597.20	586.85	517.80	465.00	379.34	392.20	0.19	0.22	0.40	0.56	0.88	0.91
	4	1879.99	1843.80	1600.74	1412.73	1105.13	1139.96	0.04	0.05	0.19	0.41	0.87	0.90
	6	3850.37	3773.51	3245.78	2845.82	2167.19	2234.16	0.00	0.01	0.09	0.32	0.86	0.91
	8	6608.59	6472.69	5551.89	4845.18	3653.44	3754.18	0.00	0.00	0.04	0.26	0.87	0.91
	10	10009.74	9791.22	8394.53	7317.10	5491.51	5649.70	0.00	0.00	0.02	0.22	0.86	0.91
m = 30	2	704.05	673.18	508.40	404.04	248.15	232.44	0.18	0.21	0.43	0.62	0.88	0.90
	4	2035.32	1942.64	1444.10	1131.92	682.09	641.41	0.02	0.03	0.24	0.51	0.87	0.90
	6	4038.88	3852.94	2836.36	2200.12	1302.58	1222.62	0.00	0.00	0.14	0.44	0.88	0.90
	8	6769.45	6455.81	4744.78	3678.27	2175.85	2048.11	0.00	0.00	0.09	0.38	0.87	0.91
	10	10166.11	9703.02	7124.34	5516.35	3287.50	3107.41	0.00	0.00	0.05	0.35	0.87	0.90
m = 45	2	575.60	538.94	367.96	281.41	188.75	184.85	0.22	0.27	0.54	0.70	0.89	0.89
	4	1812.60	1689.95	1125.88	836.43	516.00	495.79	0.04	0.05	0.34	0.61	0.87	0.89
	6	3684.16	3435.71	2253.01	1646.54	982.84	942.15	0.00	0.01	0.24	0.54	0.87	0.89
	8	6237.52	5805.05	3783.91	2749.86	1603.62	1539.00	0.00	0.00	0.16	0.52	0.86	0.89
	10	9480.68	8818.94	5730.81	4157.02	2408.28	2303.62	0.00	0.00	0.12	0.48	0.87	0.88
m = 60	2	612.34	562.22	346.89	249.91	153.49	147.42	0.22	0.26	0.58	0.74	0.89	0.90
	4	1825.32	1663.39	987.93	686.22	390.38	374.69	0.04	0.05	0.43	0.69	0.89	0.90
	6	3733.61	3398.16	1983.81	1350.74	736.37	698.40	0.00	0.01	0.31	0.62	0.87	0.89
	8	6253.70	5692.84	3291.38	2227.96	1194.29	1132.67	0.00	0.00	0.23	0.58	0.87	0.89
	10	9485.00	8631.28	4982.57	3362.66	1801.36	1706.86	0.00	0.00	0.19	0.54	0.87	0.88
m = 75	2	576.84	517.76	287.07	199.37	128.54	126.38	0.23	0.30	0.64	0.80	0.90	0.90
	4	1753.90	1564.10	830.60	551.38	315.15	305.71	0.03	0.07	0.48	0.73	0.90	0.90
	6	3578.97	3188.50	1662.19	1079.11	588.18	564.70	0.00	0.01	0.37	0.69	0.88	0.90
	8	6022.86	5357.33	2764.16	1773.38	942.25	904.50	0.00	0.00	0.30	0.66	0.88	0.89
	10	9231.66	8199.76	4234.84	2707.73	1408.21	1344.11	0.00	0.00	0.23	0.61	0.88	0.90
m = 150	2	513.59	423.65	180.91	125.28	91.27	89.55	0.26	0.38	0.77	0.85	0.92	0.92
	4	1554.23	1266.27	494.35	314.74	206.87	203.20	0.06	0.14	0.65	0.84	0.90	0.89
	6	3188.61	2584.62	972.14	596.75	365.17	355.44	0.01	0.04	0.58	0.80	0.90	0.90
	8	5398.75	4375.76	1622.67	972.68	572.74	553.29	0.00	0.01	0.51	0.77	0.89	0.89
	10	8097.94	6549.42	2391.04	1409.78	812.16	785.43	0.00	0.01	0.44	0.74	0.88	0.88

Scenario 3: $T_{expected}$ at 3 months

	Time Point (in month)	Median Precision at V(λ) = 0.0005	0.001	0.005	0.01	0.05	0.1	Correct Coverage at V(λ) = 0.0005	0.001	0.005	0.01	0.05	0.1
Prior	2	103.25	103.46	103.33	103.67	104.30	105.25	0.81	0.80	0.80	0.81	0.82	0.84
	4	301.01	300.96	301.00	302.34	302.55	305.14	0.65	0.66	0.67	0.67	0.68	0.71
	6	597.51	597.88	597.65	597.59	601.01	603.66	0.53	0.54	0.53	0.54	0.57	0.60
	8	980.47	984.33	980.89	982.76	988.83	989.74	0.43	0.41	0.43	0.42	0.45	0.48
	10	1459.77	1465.23	1464.60	1462.30	1467.28	1472.52	0.28	0.29	0.28	0.29	0.31	0.34
m = 15	2	136.93	136.76	135.04	134.93	175.99	228.13	0.78	0.79	0.84	0.88	0.95	0.95
	4	358.73	354.43	347.06	345.35	464.34	623.96	0.63	0.66	0.78	0.86	0.96	0.95
	6	654.83	648.89	628.77	620.49	853.36	1182.29	0.55	0.58	0.75	0.87	0.97	0.96
	8	1065.81	1057.52	1015.78	999.95	1395.72	1955.59	0.42	0.47	0.74	0.87	0.96	0.95
	10	1545.54	1533.66	1469.20	1446.57	2052.19	2914.63	0.32	0.37	0.71	0.89	0.97	0.96
m = 30	2	156.62	155.59	144.06	138.35	152.29	173.21	0.78	0.77	0.83	0.88	0.92	0.92
	4	381.39	377.34	344.23	325.69	382.89	456.07	0.64	0.67	0.80	0.87	0.93	0.92
	6	685.87	673.99	603.43	568.20	689.16	844.02	0.56	0.58	0.79	0.88	0.94	0.92
	8	1095.36	1072.04	958.35	899.58	1123.30	1386.47	0.40	0.46	0.76	0.87	0.94	0.93
	10	1587.23	1554.01	1388.30	1309.69	1679.28	2090.93	0.31	0.39	0.73	0.87	0.93	0.93
m = 45	2	132.61	129.51	118.63	114.35	135.90	154.15	0.79	0.79	0.86	0.90	0.92	0.90
	4	349.03	340.68	300.54	286.67	346.36	396.86	0.66	0.68	0.82	0.87	0.92	0.91
	6	638.78	621.59	539.05	509.29	635.34	741.03	0.57	0.62	0.79	0.86	0.92	0.91
	8	1018.51	989.59	848.81	798.38	1012.04	1189.16	0.45	0.53	0.78	0.86	0.91	0.91
	10	1496.14	1454.31	1244.59	1172.34	1505.54	1775.50	0.35	0.42	0.74	0.86	0.91	0.90
m = 60	2	140.26	136.38	120.03	112.99	120.58	128.62	0.79	0.81	0.88	0.90	0.92	0.91
	4	345.16	332.74	280.51	260.15	288.86	316.00	0.67	0.71	0.84	0.89	0.91	0.91
	6	645.83	619.80	508.64	464.57	523.28	583.30	0.56	0.62	0.81	0.87	0.91	0.90
	8	1021.20	980.18	792.43	722.38	835.42	936.40	0.46	0.53	0.80	0.87	0.90	0.91
	10	1514.85	1451.47	1171.15	1067.92	1244.61	1402.95	0.35	0.43	0.75	0.86	0.91	0.90
m = 75	2	133.53	128.56	108.53	102.42	108.53	116.40	0.80	0.82	0.87	0.90	0.90	0.90
	4	335.02	321.90	254.43	233.33	250.68	272.93	0.68	0.71	0.86	0.89	0.92	0.91
	6	623.64	594.90	457.55	412.94	452.34	493.23	0.56	0.62	0.82	0.88	0.92	0.91
	8	991.74	942.08	712.83	640.22	708.23	780.47	0.46	0.54	0.81	0.88	0.91	0.91
	10	1495.33	1415.91	1064.74	948.44	1044.27	1152.45	0.34	0.45	0.76	0.87	0.91	0.90
m = 150	2	123.20	115.47	90.46	84.10	85.74	87.50	0.82	0.84	0.90	0.91	0.91	0.92
	4	311.33	286.35	205.31	184.72	190.65	194.63	0.71	0.76	0.88	0.90	0.90	0.90
	6	594.69	540.59	367.38	321.47	326.62	334.92	0.59	0.66	0.85	0.89	0.90	0.90
	8	966.52	876.24	582.41	501.68	504.81	519.16	0.47	0.57	0.83	0.88	0.89	0.88
	10	1401.16	1268.57	821.04	703.21	712.32	737.27	0.38	0.50	0.81	0.88	0.89	0.88

Scenario 4: $T_{expected}$ at 0 months

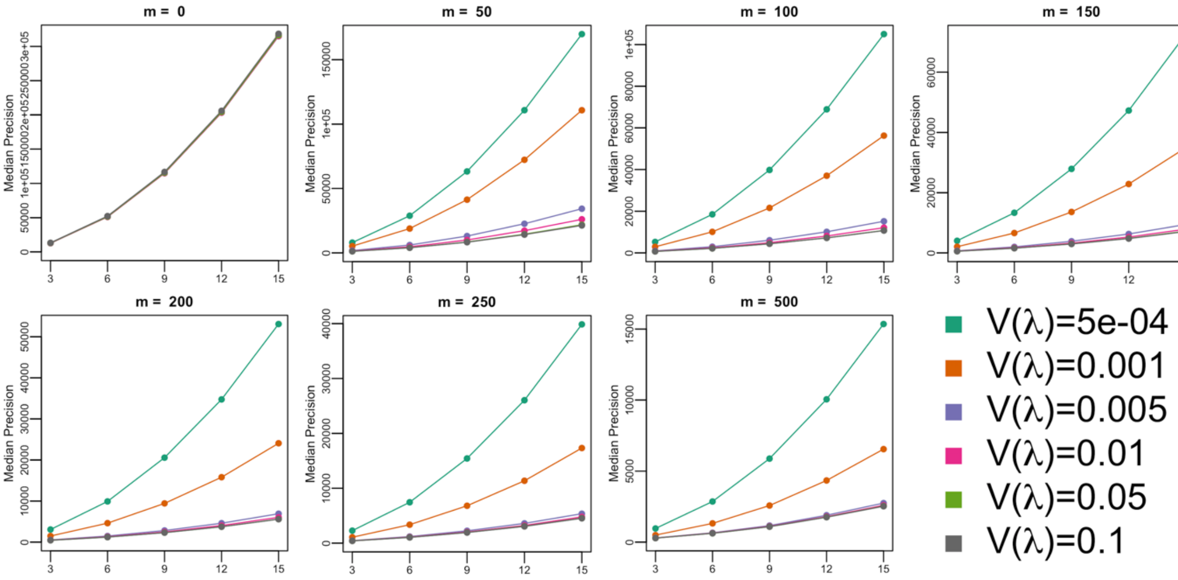


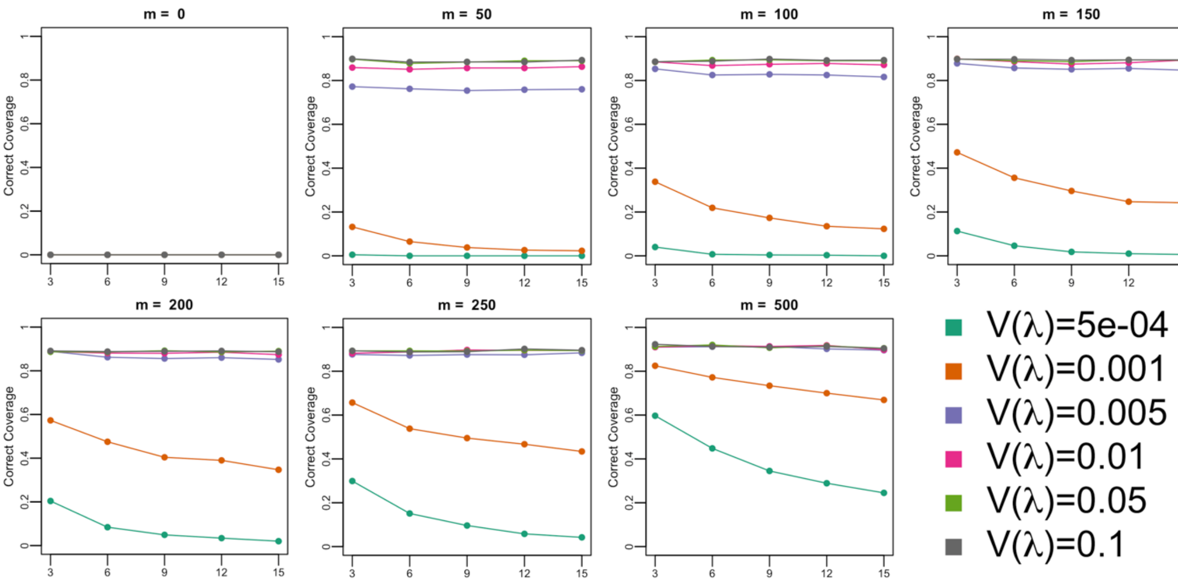


	Time Point (in month)	Median Precision at V(λ) = 0.0005	0.001	0.005	0.01	0.05	0.1	Correct Coverage at V(λ) = 0.0005	0.001	0.005	0.01	0.05	0.1
Prior	2	52.11	52.50	52.33	52.30	52.71	52.38	0.88	0.89	0.89	0.89	0.90	0.91
	4	89.81	90.03	90.55	89.40	90.26	89.06	0.90	0.90	0.90	0.90	0.91	0.92
	6	130.76	130.90	130.42	129.75	130.44	129.91	0.91	0.92	0.91	0.91	0.92	0.93
	8	159.34	160.31	159.92	159.90	160.11	159.08	0.92	0.93	0.94	0.92	0.93	0.94
	10	184.22	184.20	183.61	183.93	183.96	182.81	0.93	0.93	0.93	0.93	0.94	0.95
m = 15	2	58.41	57.84	58.75	60.34	85.09	123.05	0.90	0.89	0.92	0.93	0.96	0.96
	4	103.90	103.50	104.78	109.46	186.37	305.68	0.91	0.91	0.93	0.96	0.98	0.97
	6	135.18	133.98	135.64	143.56	294.63	535.32	0.93	0.94	0.97	0.98	0.98	0.97
	8	160.92	159.89	162.07	174.11	431.84	846.16	0.94	0.94	0.97	0.99	0.99	0.98
	10	175.14	173.46	178.06	198.14	597.25	1231.71	0.96	0.96	0.99	0.99	0.99	0.98
m = 30	2	60.76	60.96	62.29	64.83	93.76	122.47	0.91	0.92	0.94	0.94	0.95	0.95
	4	103.22	103.26	106.33	113.68	203.04	294.86	0.92	0.92	0.95	0.97	0.96	0.94
	6	131.55	131.71	136.25	147.62	325.88	515.72	0.94	0.95	0.97	0.98	0.97	0.95
	8	154.20	154.05	160.96	183.85	497.48	824.02	0.95	0.95	0.98	0.98	0.97	0.96
	10	174.68	175.28	188.79	226.45	723.14	1231.36	0.96	0.96	0.99	0.99	0.98	0.95
m = 45	2	56.58	56.30	58.26	62.75	97.42	122.09	0.91	0.91	0.93	0.93	0.92	0.91
	4	97.24	97.80	103.70	117.00	222.26	296.14	0.93	0.93	0.96	0.96	0.94	0.92
	6	133.10	133.28	145.00	170.96	385.18	539.32	0.93	0.94	0.96	0.96	0.95	0.93
	8	157.22	158.89	179.06	222.51	586.29	848.94	0.95	0.95	0.97	0.98	0.95	0.93
	10	184.16	187.77	221.92	288.95	853.04	1255.06	0.95	0.96	0.98	0.97	0.95	0.93
m = 60	2	58.91	58.60	61.42	64.90	92.88	109.16	0.91	0.92	0.93	0.93	0.92	0.92
	4	97.88	98.34	104.42	118.05	204.69	255.97	0.92	0.93	0.94	0.95	0.94	0.92
	6	130.22	129.35	143.00	168.78	348.75	456.65	0.94	0.93	0.96	0.97	0.94	0.93
	8	151.39	152.47	177.12	223.21	536.36	721.40	0.95	0.95	0.97	0.97	0.94	0.93
	10	184.68	186.64	229.16	301.22	791.02	1076.59	0.95	0.96	0.97	0.97	0.95	0.93
m = 75	2	62.83	63.10	65.80	69.50	93.83	104.88	0.90	0.90	0.91	0.91	0.91	0.90
	4	100.39	100.98	109.85	122.30	197.40	234.80	0.91	0.92	0.93	0.94	0.93	0.91
	6	131.99	133.50	151.45	177.09	335.09	414.84	0.93	0.93	0.95	0.96	0.93	0.92
	8	154.76	157.76	188.95	236.60	511.40	646.02	0.95	0.95	0.97	0.96	0.93	0.91
	10	182.52	186.52	235.90	310.66	734.17	943.51	0.95	0.96	0.97	0.97	0.94	0.92
m = 150	2	55.81	56.40	60.32	65.25	79.78	84.13	0.92	0.92	0.92	0.92	0.92	0.92
	4	95.71	97.11	110.15	124.95	170.46	184.01	0.92	0.92	0.93	0.92	0.91	0.91
	6	129.19	132.34	160.07	190.18	283.55	313.38	0.92	0.94	0.94	0.93	0.91	0.90
	8	157.67	164.43	213.97	266.00	428.51	479.05	0.94	0.95	0.94	0.94	0.91	0.90
	10	187.08	196.64	272.57	352.85	600.74	674.45	0.95	0.95	0.94	0.94	0.91	0.90

6.1.4 Annexe 2.3 Third Setting

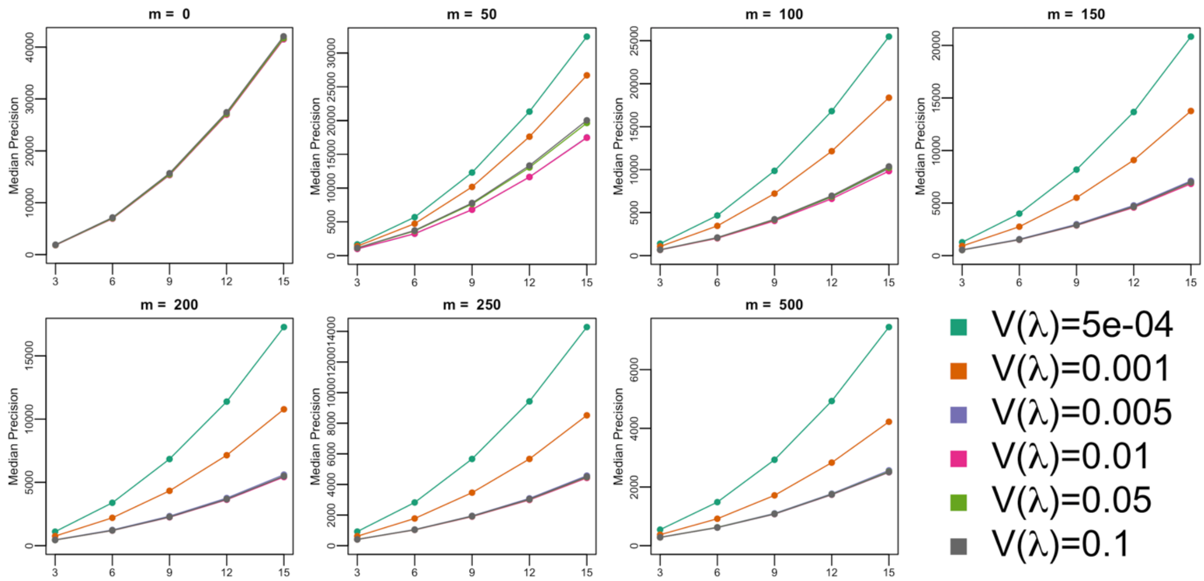
Scenario 1: $T_{expected}$ at 12 months

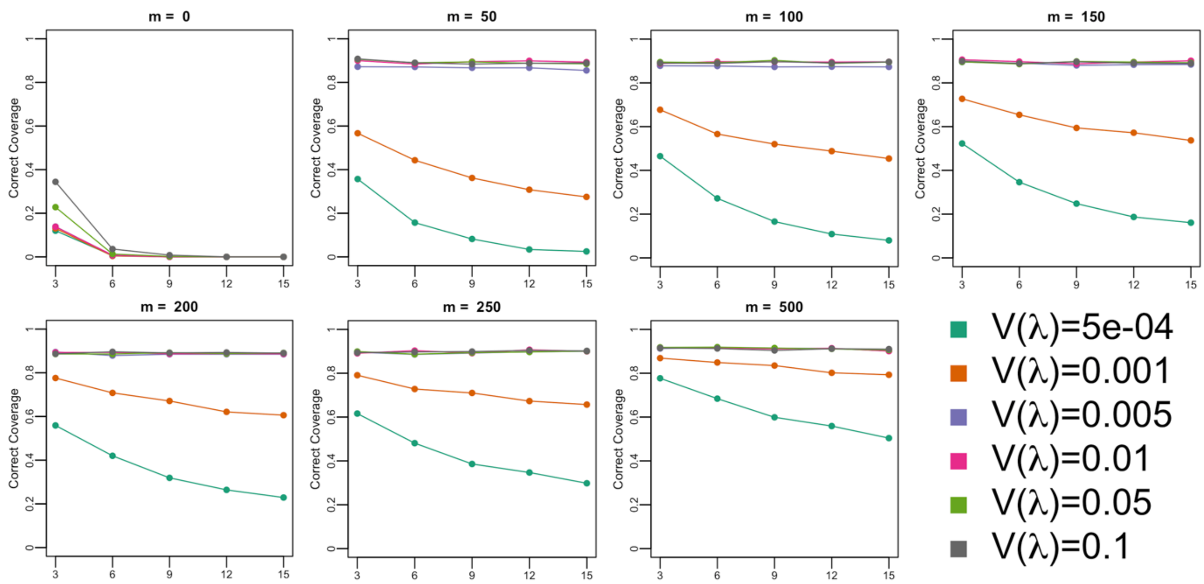




	Time Point (in month)	Median Precision at V(λ) = 0.0005	0.001	0.005	0.01	0.05	0.1	Correct Coverage at V(λ) = 0.0005	0.001	0.005	0.01	0.05	0.1
Prior	3	12749.41	12748.54	12756.22	12790.37	12972.43	13227.75	0.00	0.00	0.00	0.00	0.00	0.00
	6	51129.97	51103.89	51127.51	51183.26	51581.78	52233.08	0.00	0.00	0.00	0.00	0.00	0.00
	9	114949.30	114896.70	114919.40	114965.60	115583.70	116712.50	0.00	0.00	0.00	0.00	0.00	0.00
	12	203389.70	203366.00	203421.70	203557.90	204339.00	205951.40	0.00	0.00	0.00	0.00	0.00	0.00
	15	314979.50	315060.50	315052.00	315222.70	316285.90	318402.00	0.00	0.00	0.00	0.00	0.00	0.00
m = 50	3	7965.71	5247.37	1773.12	1407.43	1227.36	1209.60	0.01	0.13	0.77	0.86	0.90	0.90
	6	28840.89	18868.01	6093.36	4719.27	4033.41	3962.16	0.00	0.06	0.76	0.85	0.88	0.88
	9	63241.77	41304.90	13066.55	10000.68	8449.47	8296.12	0.00	0.04	0.75	0.86	0.88	0.88
	12	110821.60	72295.35	22627.31	17249.82	14490.99	14192.85	0.00	0.03	0.76	0.86	0.89	0.88
	15	169905.90	110794.70	34292.32	26058.74	21817.67	21335.67	0.00	0.02	0.76	0.86	0.89	0.89
m = 100	3	5246.59	2915.47	930.75	781.69	709.26	706.65	0.04	0.34	0.85	0.88	0.88	0.89
	6	18493.04	10101.98	2959.12	2421.95	2177.14	2164.28	0.01	0.22	0.82	0.87	0.89	0.89
	9	39793.18	21580.30	6070.73	4902.89	4392.41	4368.36	0.00	0.17	0.83	0.87	0.89	0.90
	12	68902.50	37039.60	10108.72	8098.48	7222.18	7186.11	0.00	0.14	0.82	0.88	0.89	0.89
	15	105014.20	56268.41	15169.12	12092.60	10774.22	10709.33	0.00	0.12	0.82	0.87	0.89	0.89
m = 150	3	4014.09	2047.64	682.44	594.40	549.13	542.18	0.11	0.47	0.88	0.90	0.90	0.90
	6	13317.34	6593.54	1978.73	1694.84	1569.84	1546.92	0.05	0.36	0.86	0.89	0.89	0.90
	9	27887.22	13591.08	3857.69	3255.01	2992.96	2953.93	0.02	0.30	0.85	0.88	0.89	0.89
	12	47261.62	22851.47	6268.40	5256.55	4819.31	4752.10	0.01	0.25	0.86	0.88	0.89	0.89
	15	72645.65	34948.88	9434.44	7868.67	7199.91	7096.93	0.01	0.24	0.85	0.89	0.89	0.89
m = 200	3	3068.73	1484.95	537.26	482.47	456.72	455.07	0.20	0.57	0.89	0.89	0.89	0.89
	6	9910.49	4619.49	1479.64	1308.83	1225.58	1223.32	0.08	0.48	0.86	0.88	0.89	0.89
	9	20569.44	9433.19	2826.57	2485.22	2315.14	2309.71	0.05	0.40	0.86	0.88	0.89	0.89
	12	34746.90	15805.92	4601.13	4038.78	3755.01	3744.20	0.03	0.39	0.86	0.88	0.89	0.89
	15	53099.86	24075.99	6915.69	6035.07	5610.35	5589.29	0.02	0.35	0.85	0.87	0.89	0.89
m = 250	3	2273.67	1076.43	452.08	425.00	415.38	413.92	0.30	0.66	0.88	0.88	0.89	0.89
	6	7446.57	3361.41	1195.15	1097.70	1051.51	1044.15	0.15	0.54	0.87	0.89	0.89	0.89
	9	15431.60	6807.35	2246.15	2029.56	1950.04	1932.49	0.10	0.50	0.88	0.90	0.89	0.89
	12	26042.97	11365.08	3596.94	3218.92	3079.96	3055.45	0.06	0.47	0.88	0.90	0.90	0.90
	15	39865.42	17326.76	5361.56	4785.79	4558.12	4529.89	0.04	0.43	0.88	0.90	0.89	0.90
m = 500	3	960.37	495.15	294.17	287.56	283.36	284.31	0.60	0.82	0.91	0.91	0.91	0.92
	6	2859.23	1319.24	655.04	634.69	620.16	622.80	0.45	0.77	0.91	0.92	0.92	0.91
	9	5878.89	2576.06	1162.81	1111.38	1088.79	1087.70	0.34	0.73	0.91	0.91	0.91	0.91
	12	10051.42	4340.08	1891.24	1792.44	1759.52	1754.60	0.29	0.70	0.90	0.92	0.92	0.91
	15	15351.03	6547.27	2747.32	2593.77	2537.95	2526.93	0.24	0.67	0.90	0.90	0.90	0.90

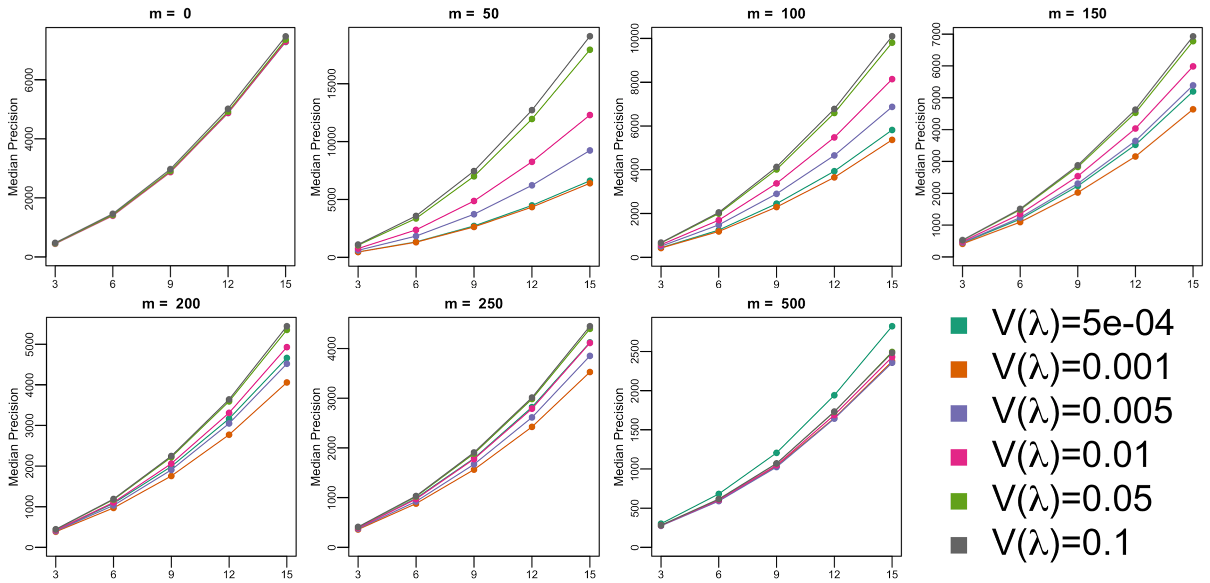
Scenario 2: $T_{expected}$ at 6 months

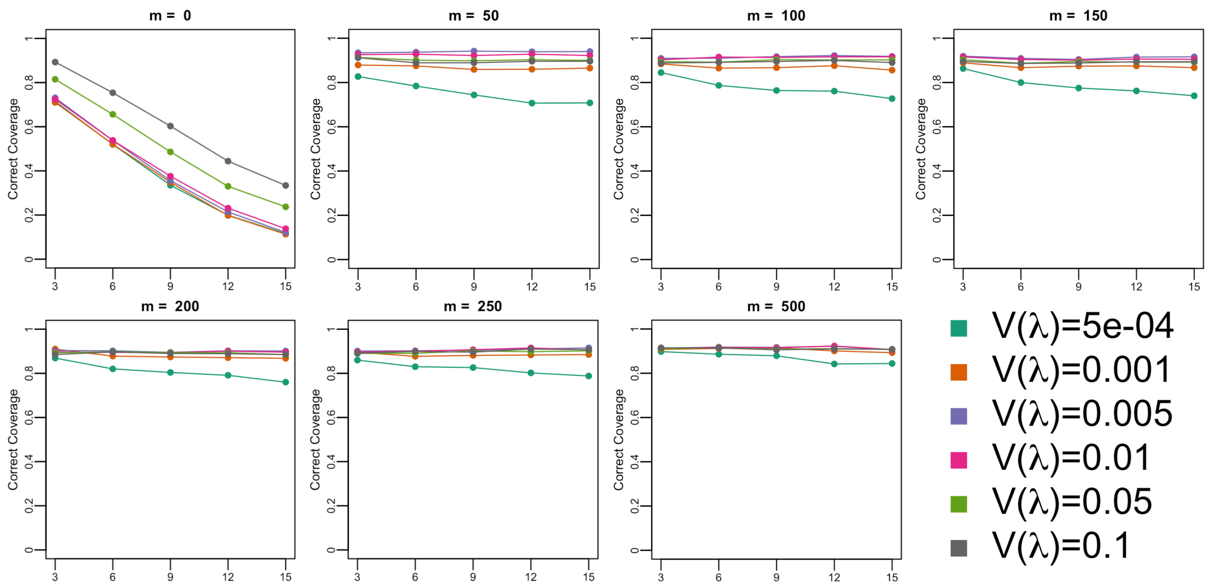




	Time Point (in month)	Median Precision at V(λ) =						Correct Coverage at V(λ) =					
		0.0005	0.001	0.005	0.01	0.05	0.1	0.0005	0.001	0.005	0.01	0.05	0.1
Prior	3	1819.00	1819.84	1824.28	1829.74	1863.01	1911.08	0.12	0.13	0.14	0.14	0.23	0.34
	6	6948.67	6946.59	6951.38	6961.80	7031.09	7154.96	0.01	0.00	0.01	0.01	0.01	0.04
	9	15343.78	15332.50	15351.33	15367.38	15467.71	15682.67	0.00	0.00	0.00	0.00	0.00	0.01
	12	27012.12	26970.39	27006.36	27011.37	27155.09	27431.34	0.00	0.00	0.00	0.00	0.00	0.00
	15	41513.99	41511.32	41524.78	41532.31	41713.66	42076.16	0.00	0.00	0.00	0.00	0.00	0.00
m = 50	3	1658.06	1393.38	989.32	1002.17	1121.36	1141.63	0.36	0.57	0.87	0.90	0.91	0.91
	6	5692.52	4728.28	3234.01	3253.63	3651.95	3726.39	0.16	0.44	0.87	0.88	0.89	0.89
	9	12299.71	10169.65	6800.21	6803.92	7637.45	7787.38	0.08	0.36	0.87	0.90	0.89	0.88
	12	21325.53	17609.02	11645.26	11639.09	13057.23	13332.58	0.03	0.31	0.87	0.90	0.89	0.89
	15	32430.18	26703.71	17507.07	17454.06	19638.38	20030.38	0.02	0.28	0.86	0.89	0.88	0.89
m = 100	3	1390.17	1057.84	673.42	660.03	676.63	687.27	0.46	0.68	0.88	0.89	0.90	0.89
	6	4667.55	3456.38	2062.08	2013.21	2072.07	2102.16	0.27	0.57	0.88	0.90	0.89	0.89
	9	9860.31	7215.33	4146.22	4043.53	4172.00	4229.49	0.17	0.52	0.87	0.90	0.90	0.90
	12	16807.05	12143.72	6803.99	6607.56	6851.23	6957.31	0.11	0.49	0.87	0.90	0.89	0.89
	15	25473.67	18368.08	10125.36	9831.79	10220.76	10368.49	0.08	0.45	0.87	0.90	0.90	0.90
m = 150	3	1270.39	908.51	555.30	534.79	533.35	534.01	0.52	0.73	0.90	0.91	0.90	0.90
	6	3999.56	2751.74	1558.80	1505.02	1520.47	1525.04	0.35	0.65	0.89	0.90	0.89	0.89
	9	8183.64	5508.27	2978.99	2866.74	2894.11	2909.60	0.25	0.59	0.88	0.89	0.90	0.90
	12	13668.01	9090.97	4772.65	4579.64	4653.34	4683.48	0.19	0.57	0.88	0.90	0.90	0.89
	15	20843.13	13766.35	7112.22	6833.47	6967.13	7005.77	0.16	0.54	0.88	0.90	0.89	0.89
m = 200	3	1106.64	755.13	463.76	449.90	448.77	448.73	0.56	0.78	0.90	0.89	0.89	0.89
	6	3387.58	2199.66	1237.50	1192.98	1201.74	1202.11	0.42	0.71	0.88	0.89	0.89	0.90
	9	6841.97	4332.27	2328.15	2242.09	2265.31	2264.67	0.32	0.67	0.88	0.89	0.89	0.89
	12	11379.78	7143.28	3758.44	3627.56	3673.60	3668.66	0.26	0.62	0.88	0.89	0.89	0.89
	15	17268.61	10775.71	5604.97	5423.40	5489.91	5482.59	0.23	0.61	0.88	0.89	0.89	0.89
m = 250	3	920.47	616.02	409.74	406.43	410.85	412.54	0.62	0.79	0.90	0.89	0.90	0.89
	6	2820.26	1775.13	1051.54	1029.13	1037.20	1043.72	0.48	0.73	0.89	0.90	0.89	0.90
	9	5664.02	3461.84	1945.13	1894.50	1917.09	1932.00	0.39	0.71	0.89	0.89	0.89	0.90
	12	9424.81	5664.87	3086.29	2985.12	3023.22	3041.63	0.35	0.67	0.90	0.91	0.90	0.90
	15	14278.09	8513.51	4569.99	4424.97	4478.15	4505.31	0.30	0.66	0.90	0.90	0.90	0.90
m = 500	3	545.26	374.06	286.30	282.90	283.08	282.49	0.78	0.87	0.91	0.92	0.92	0.92
	6	1483.15	917.11	626.59	618.93	622.25	615.89	0.68	0.85	0.92	0.92	0.92	0.91
	9	2927.76	1713.51	1098.74	1074.87	1082.17	1077.95	0.60	0.84	0.91	0.91	0.92	0.90
	12	4927.99	2828.76	1769.79	1735.66	1747.44	1740.98	0.56	0.80	0.91	0.91	0.91	0.91
	15	7448.35	4221.21	2562.49	2501.76	2520.24	2506.24	0.50	0.79	0.90	0.90	0.91	0.91

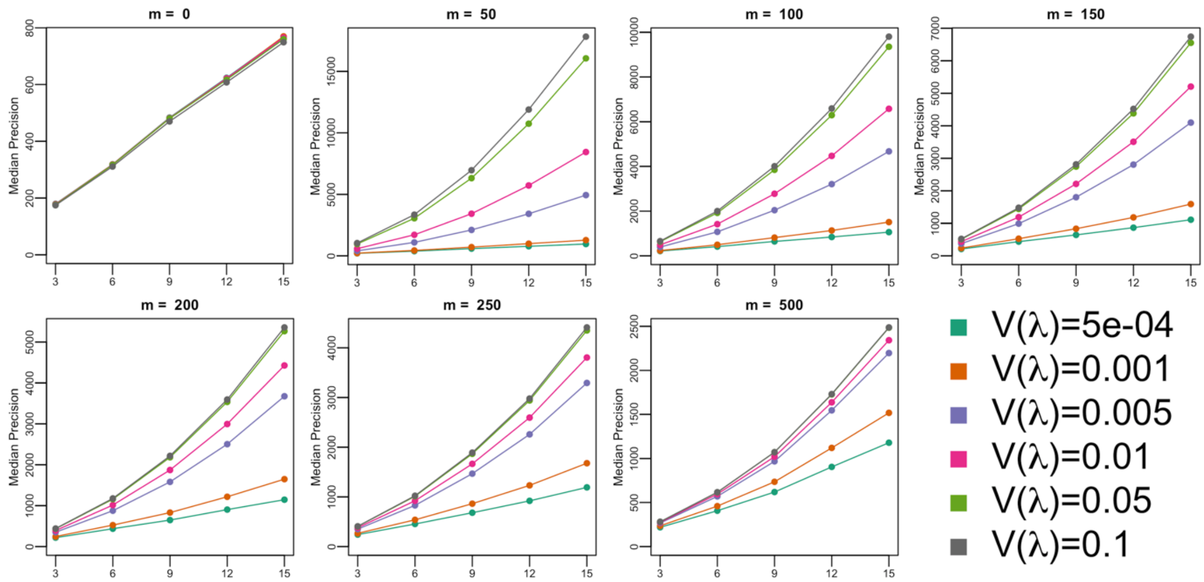
Scenario 3: $T_{expected}$ at 3 months

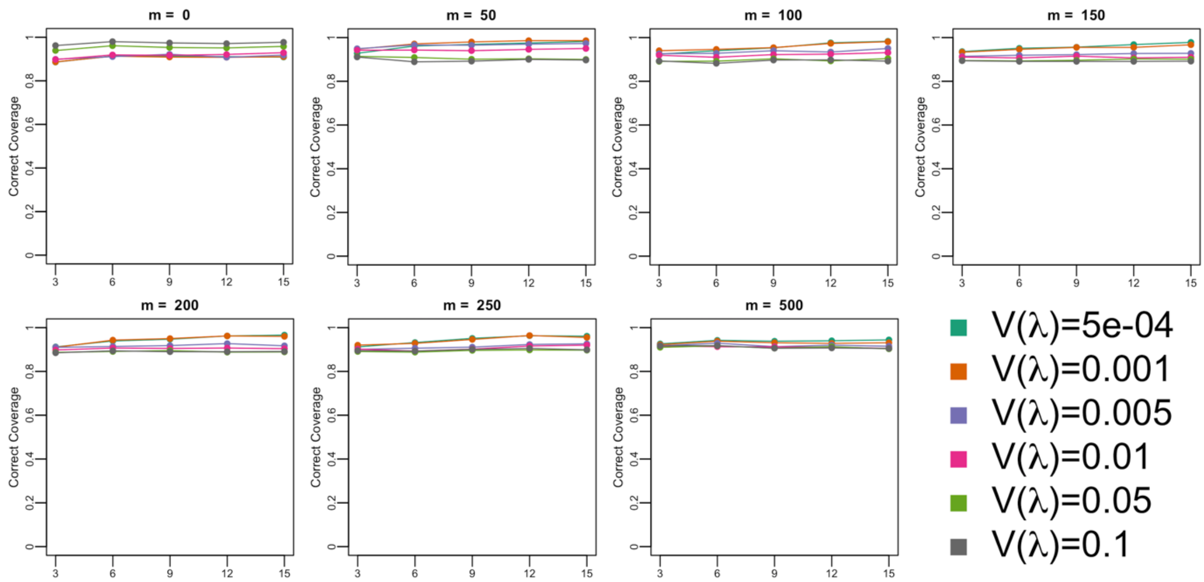




	Time Point (in month)	Median Precision at V(λ) = 0.0005	0.001	0.005	0.01	0.05	0.1	Correct Coverage at V(λ) = 0.0005	0.001	0.005	0.01	0.05	0.1
Prior	3	446.83	447.15	449.11	450.26	460.38	476.75	0.72	0.71	0.73	0.72	0.82	0.89
	6	1398.15	1398.30	1403.03	1403.97	1422.59	1461.12	0.52	0.52	0.54	0.54	0.66	0.75
	9	2873.73	2873.68	2881.75	2880.79	2909.30	2972.70	0.34	0.35	0.36	0.38	0.49	0.60
	12	4872.20	4882.70	4889.43	4877.71	4920.34	5015.95	0.20	0.20	0.21	0.23	0.33	0.44
	15	7278.38	7293.57	7307.86	7294.95	7357.21	7467.54	0.12	0.11	0.12	0.14	0.24	0.33
m = 50	3	467.39	456.85	605.82	758.67	1044.18	1103.25	0.83	0.88	0.93	0.93	0.91	0.91
	6	1333.92	1304.47	1835.55	2368.97	3360.44	3576.87	0.78	0.88	0.94	0.93	0.90	0.89
	9	2711.72	2625.83	3723.99	4867.29	6998.19	7453.54	0.74	0.86	0.94	0.92	0.90	0.89
	12	4485.27	4341.22	6222.72	8254.93	11953.28	12718.79	0.71	0.86	0.94	0.93	0.90	0.90
	15	6615.89	6399.84	9236.15	12295.00	17937.06	19106.42	0.71	0.86	0.94	0.92	0.90	0.90
m = 100	3	439.45	423.19	507.42	574.02	655.00	671.40	0.84	0.88	0.91	0.90	0.89	0.89
	6	1246.11	1181.90	1482.75	1698.89	1998.88	2050.55	0.79	0.86	0.91	0.92	0.89	0.89
	9	2450.21	2295.98	2901.39	3377.12	4013.93	4130.04	0.76	0.87	0.92	0.91	0.90	0.90
	12	3934.23	3651.98	4655.45	5479.56	6592.85	6778.73	0.76	0.88	0.92	0.92	0.90	0.90
	15	5817.54	5365.30	6873.15	8140.79	9805.69	10101.13	0.73	0.86	0.92	0.92	0.90	0.89
m = 150	3	440.56	411.73	453.56	484.46	523.72	529.47	0.86	0.89	0.92	0.92	0.90	0.90
	6	1186.37	1093.77	1237.00	1347.38	1483.05	1508.92	0.80	0.87	0.91	0.90	0.89	0.89
	9	2228.36	2022.67	2304.27	2537.35	2826.26	2877.65	0.78	0.87	0.90	0.90	0.90	0.89
	12	3521.27	3155.74	3643.86	4034.02	4528.28	4626.79	0.76	0.88	0.92	0.91	0.89	0.89
	15	5199.41	4638.34	5389.77	5986.07	6777.14	6928.02	0.74	0.87	0.92	0.90	0.89	0.89
m = 200	3	413.69	383.65	401.45	421.06	440.86	444.73	0.87	0.91	0.90	0.90	0.89	0.88
	6	1082.82	969.97	1032.54	1106.02	1174.98	1190.24	0.82	0.88	0.90	0.90	0.90	0.90
	9	1989.74	1756.07	1906.35	2061.18	2218.93	2247.34	0.80	0.87	0.90	0.89	0.89	0.89
	12	3166.02	2771.73	3049.16	3310.09	3592.66	3640.53	0.79	0.87	0.90	0.90	0.89	0.89
	15	4661.82	4059.04	4519.20	4927.92	5352.12	5442.91	0.76	0.87	0.90	0.90	0.88	0.88
m = 250	3	386.42	358.70	374.90	391.39	407.35	411.08	0.86	0.90	0.90	0.90	0.89	0.89
	6	987.23	879.57	922.61	971.21	1020.76	1032.53	0.83	0.88	0.90	0.90	0.89	0.90
	9	1789.82	1563.23	1669.83	1776.00	1885.19	1908.91	0.83	0.88	0.90	0.91	0.90	0.90
	12	2820.82	2423.43	2613.80	2790.13	2983.73	3013.06	0.80	0.88	0.91	0.92	0.90	0.91
	15	4123.39	3526.83	3851.84	4111.98	4395.86	4448.88	0.79	0.88	0.92	0.91	0.90	0.91
m = 500	3	301.70	276.51	274.32	279.01	282.24	281.62	0.90	0.91	0.91	0.91	0.91	0.92
	6	681.44	599.25	590.02	603.75	616.25	615.19	0.89	0.91	0.92	0.92	0.92	0.91
	9	1206.17	1037.36	1024.86	1048.01	1069.93	1071.21	0.88	0.92	0.92	0.92	0.91	0.91
	12	1941.52	1650.72	1642.44	1688.84	1728.97	1732.71	0.84	0.90	0.92	0.92	0.91	0.91
	15	2822.39	2373.80	2356.21	2429.00	2494.32	2483.59	0.84	0.89	0.91	0.91	0.91	0.91

Scenario 4: $T_{expected}$ at 0 months

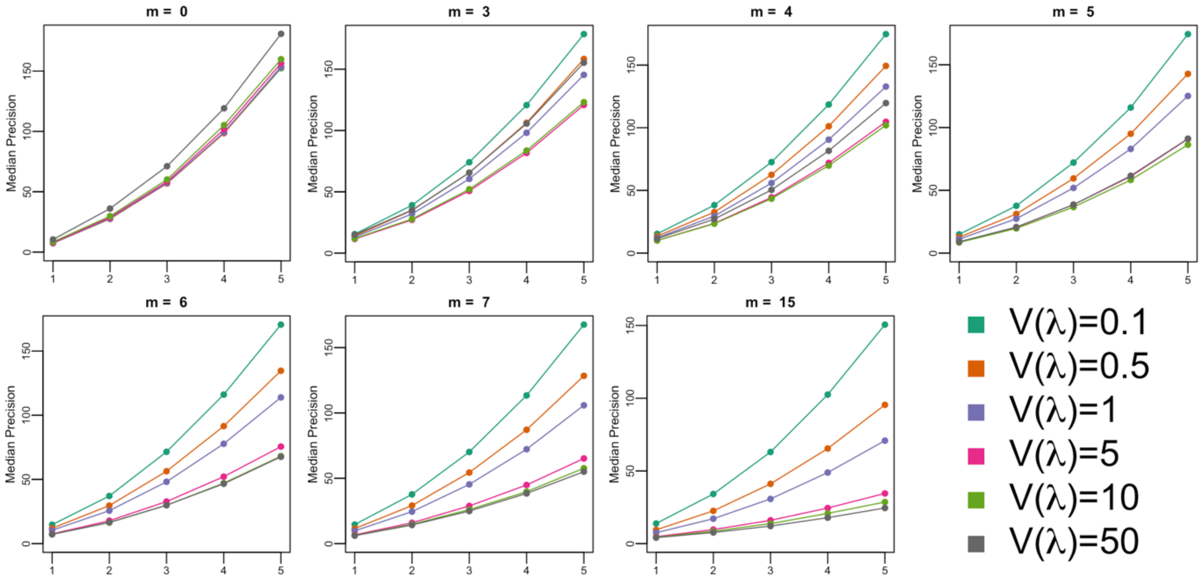


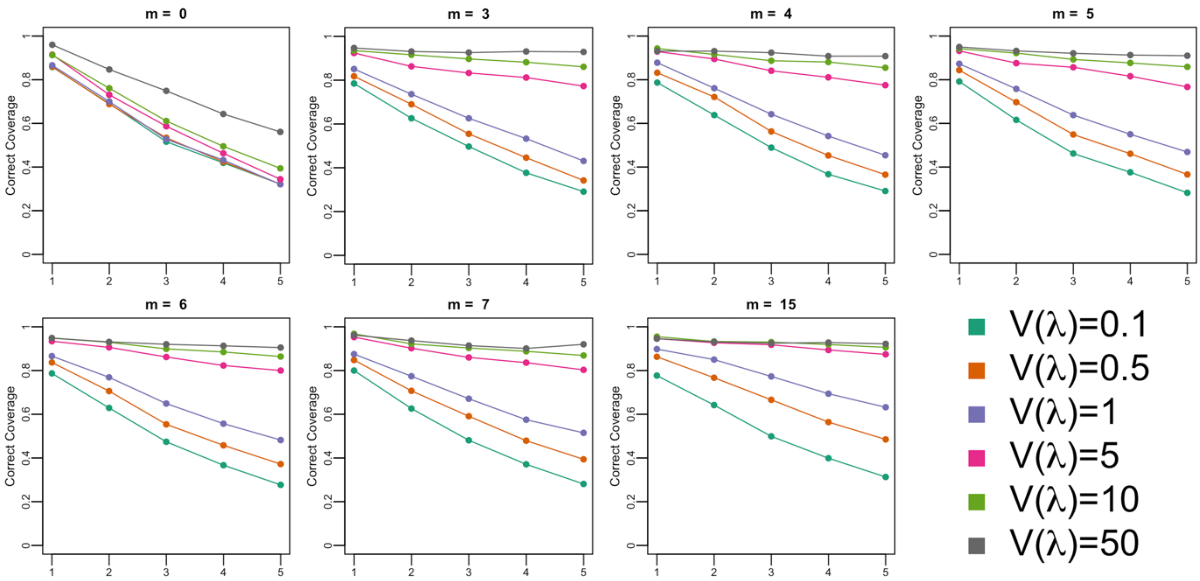


	Time Point (in month)	Median Precision at V(λ) = 0.0005	0.001	0.005	0.01	0.05	0.1	Correct Coverage at V(λ) = 0.0005	0.001	0.005	0.01	0.05	0.1
Prior	3	179.60	178.01	177.13	178.08	176.44	174.57	0.89	0.89	0.90	0.90	0.94	0.96
	6	318.66	318.59	317.65	316.89	316.68	311.05	0.91	0.91	0.91	0.92	0.96	0.98
	9	483.64	482.50	481.77	480.10	480.03	470.01	0.91	0.91	0.92	0.92	0.95	0.97
	12	623.70	620.37	620.33	621.77	617.03	607.72	0.91	0.91	0.91	0.92	0.95	0.97
	15	768.56	769.91	763.81	765.59	759.92	749.00	0.91	0.91	0.92	0.93	0.96	0.98
m = 50	3	204.71	220.41	402.47	581.03	956.61	1036.22	0.93	0.95	0.95	0.94	0.91	0.91
	6	378.26	437.37	1093.00	1710.09	3052.32	3346.02	0.96	0.97	0.97	0.94	0.91	0.89
	9	586.15	707.16	2105.59	3425.93	6317.00	6961.37	0.97	0.98	0.96	0.94	0.90	0.89
	12	777.29	988.50	3417.82	5721.94	10745.29	11894.93	0.98	0.99	0.97	0.95	0.90	0.90
	15	960.37	1274.88	4938.11	8439.53	16060.59	17824.43	0.98	0.99	0.97	0.95	0.90	0.90
m = 100	3	212.76	235.00	392.81	489.07	633.92	657.09	0.92	0.94	0.93	0.92	0.89	0.89
	6	412.00	495.20	1071.68	1416.65	1920.14	2000.84	0.94	0.95	0.93	0.91	0.89	0.88
	9	643.40	814.87	2041.74	2776.14	3847.99	4007.80	0.95	0.95	0.94	0.92	0.90	0.90
	12	841.22	1133.05	3207.69	4469.89	6291.75	6590.71	0.98	0.97	0.93	0.92	0.89	0.90
	15	1059.69	1508.54	4672.07	6576.53	9352.44	9803.68	0.98	0.98	0.95	0.93	0.90	0.89
m = 150	3	210.06	237.98	374.96	435.94	510.04	521.21	0.94	0.93	0.91	0.91	0.90	0.89
	6	436.73	526.83	990.79	1189.63	1441.56	1479.82	0.95	0.95	0.92	0.91	0.89	0.89
	9	643.82	833.65	1802.73	2213.56	2744.50	2814.62	0.96	0.96	0.92	0.92	0.90	0.89
	12	866.86	1182.42	2806.46	3508.93	4384.07	4521.24	0.97	0.96	0.93	0.91	0.90	0.89
	15	1111.23	1591.74	4098.78	5206.63	6553.41	6743.85	0.98	0.97	0.93	0.91	0.90	0.89
m = 200	3	218.34	245.13	351.18	391.68	436.37	440.95	0.91	0.91	0.91	0.90	0.89	0.88
	6	436.83	524.76	876.56	1014.81	1158.51	1177.20	0.94	0.94	0.91	0.91	0.89	0.89
	9	647.78	830.60	1581.31	1871.38	2181.60	2216.89	0.95	0.95	0.92	0.90	0.90	0.89
	12	903.89	1217.27	2503.39	2995.62	3536.59	3594.13	0.96	0.96	0.93	0.91	0.89	0.89
	15	1145.82	1647.83	3674.54	4427.44	5266.24	5357.41	0.97	0.96	0.92	0.90	0.89	0.89
m = 250	3	241.23	266.75	350.70	378.94	404.85	407.61	0.91	0.92	0.90	0.90	0.89	0.90
	6	453.96	538.15	828.62	920.82	1012.35	1022.59	0.93	0.93	0.91	0.89	0.89	0.89
	9	681.03	862.98	1467.08	1663.98	1866.26	1889.66	0.95	0.95	0.91	0.90	0.90	0.90
	12	919.96	1231.36	2257.31	2594.42	2939.01	2977.34	0.96	0.96	0.92	0.92	0.90	0.90
	15	1191.03	1676.95	3291.44	3803.31	4347.89	4409.08	0.96	0.96	0.93	0.92	0.90	0.90
m = 500	3	219.04	235.56	267.25	274.45	280.97	281.56	0.93	0.92	0.92	0.92	0.91	0.92
	6	406.95	458.96	569.53	595.46	615.01	616.90	0.94	0.94	0.93	0.91	0.92	0.92
	9	618.90	735.20	967.52	1019.72	1071.69	1071.38	0.94	0.93	0.91	0.91	0.91	0.91
	12	904.18	1119.92	1546.14	1637.47	1727.34	1731.14	0.94	0.93	0.92	0.91	0.91	0.91
	15	1178.68	1517.67	2196.41	2341.77	2484.32	2487.61	0.94	0.93	0.92	0.90	0.90	0.90

6.1.5 Annexe 2.4 Fourth Setting

Scenario 1: $T_{expected}$ at 12 months



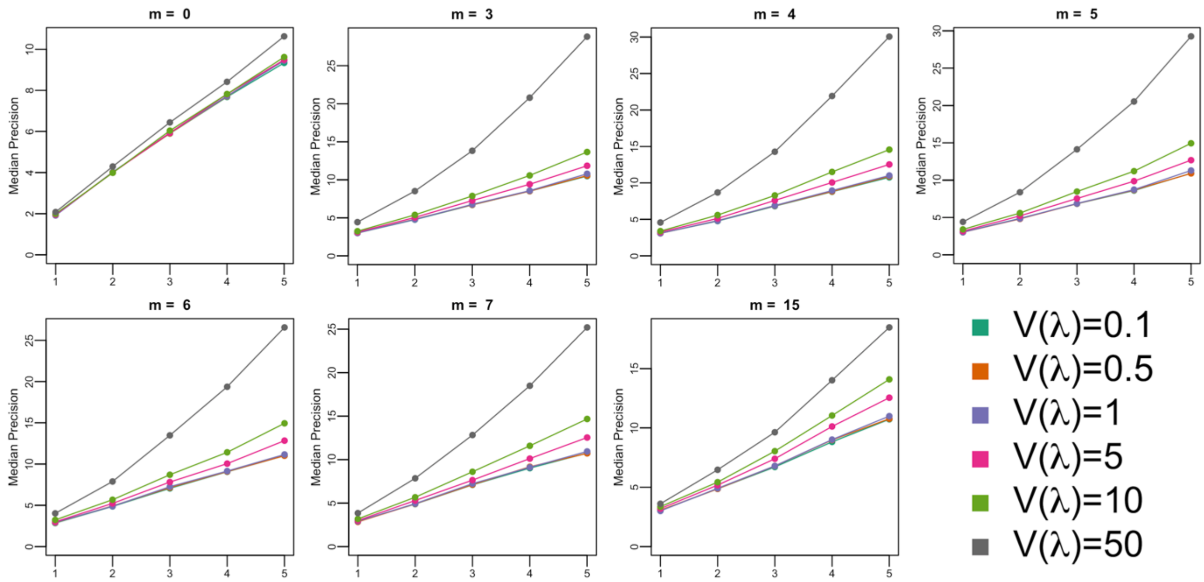


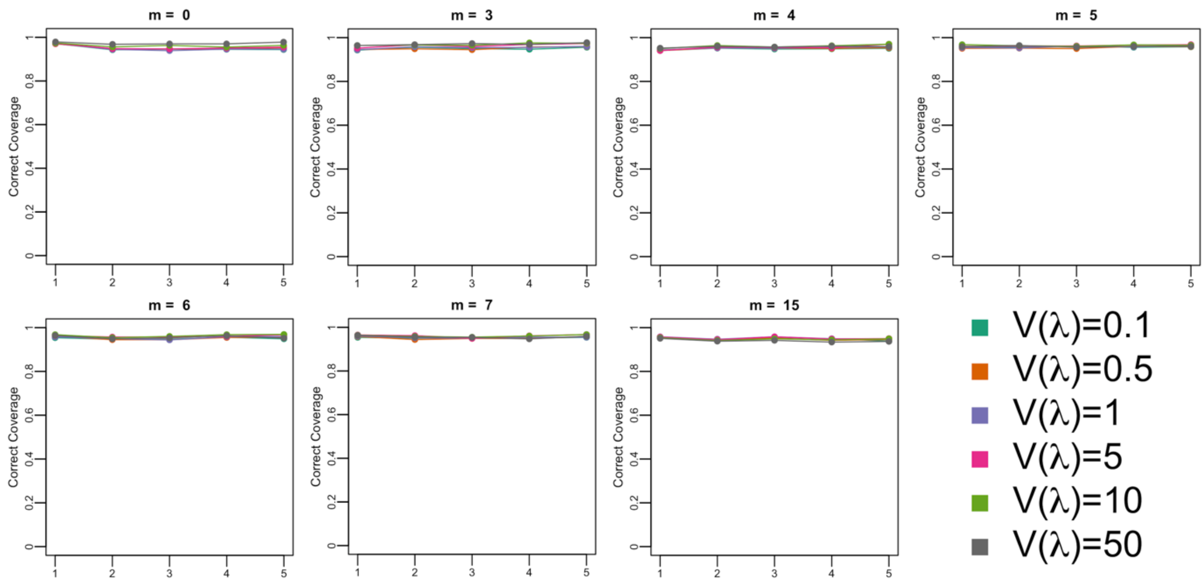
	Time Point (in month)	Median Precision at V(λ) = 0.1	0.5	1	5	10	50	Correct Coverage at V(λ) = 0.1	0.5	1	5	10	50
Prior	1	7.36	7.41	7.38	7.72	8.42	10.45	0.86	0.86	0.87	0.92	0.91	0.96
	2	27.47	27.66	28.02	28.72	29.78	36.06	0.69	0.69	0.70	0.73	0.76	0.85
	3	57.03	56.88	57.33	58.40	60.14	71.17	0.52	0.53	0.53	0.59	0.61	0.75
	4	98.62	98.60	99.34	101.87	105.24	119.15	0.42	0.42	0.43	0.46	0.50	0.64
	5	152.41	153.20	153.70	156.56	159.83	180.90	0.32	0.32	0.32	0.34	0.39	0.56
m = 3	1	15.52	13.98	13.05	11.51	11.90	14.92	0.78	0.82	0.85	0.92	0.94	0.95
	2	39.05	34.86	31.97	27.13	27.81	35.10	0.63	0.69	0.74	0.86	0.92	0.93
	3	74.15	65.66	60.53	50.73	52.11	65.62	0.50	0.56	0.63	0.83	0.90	0.93
	4	120.75	106.33	98.20	81.74	83.67	105.67	0.38	0.45	0.53	0.81	0.88	0.93
	5	178.68	158.40	145.43	120.93	123.15	155.37	0.29	0.34	0.43	0.77	0.86	0.93
m = 4	1	15.33	13.53	12.17	10.13	10.02	11.54	0.79	0.83	0.88	0.93	0.94	0.93
	2	38.23	32.67	29.55	23.72	23.45	27.14	0.64	0.72	0.76	0.90	0.92	0.93
	3	72.59	62.48	55.90	44.45	43.42	50.42	0.49	0.56	0.64	0.84	0.89	0.92
	4	118.49	101.17	90.50	71.89	69.80	81.59	0.37	0.45	0.54	0.81	0.88	0.91
	5	174.66	149.32	132.83	104.72	101.97	119.67	0.29	0.36	0.45	0.78	0.86	0.91
m = 5	1	14.92	12.63	11.10	8.75	8.46	9.02	0.79	0.84	0.87	0.93	0.94	0.95
	2	37.65	31.15	27.39	20.49	19.67	20.75	0.62	0.70	0.76	0.88	0.92	0.93
	3	72.11	59.48	51.91	38.62	36.67	38.55	0.46	0.55	0.64	0.86	0.89	0.92
	4	115.91	95.05	82.95	61.05	58.23	61.57	0.38	0.46	0.55	0.82	0.88	0.91
	5	174.41	142.78	125.15	90.92	86.33	91.13	0.28	0.37	0.47	0.77	0.86	0.91
m = 6	1	14.73	11.95	10.40	7.52	7.21	7.24	0.79	0.84	0.87	0.93	0.95	0.95
	2	37.09	29.60	25.68	17.83	16.38	16.53	0.63	0.71	0.77	0.91	0.93	0.93
	3	71.51	56.38	48.16	32.75	29.87	29.95	0.47	0.55	0.65	0.86	0.90	0.92
	4	116.09	91.49	77.78	52.14	47.09	46.63	0.37	0.46	0.56	0.82	0.88	0.91
	5	170.61	134.68	113.89	75.56	68.14	67.65	0.28	0.37	0.48	0.80	0.86	0.90
m = 7	1	14.56	11.48	9.77	6.70	6.24	6.08	0.80	0.85	0.88	0.95	0.97	0.96
	2	37.69	29.12	24.48	15.96	14.77	14.23	0.63	0.71	0.77	0.90	0.92	0.94
	3	70.15	54.39	45.31	28.81	26.03	24.92	0.48	0.59	0.67	0.86	0.90	0.91
	4	113.41	87.12	72.23	44.88	39.73	38.38	0.37	0.48	0.57	0.84	0.89	0.90
	5	167.59	128.40	105.85	65.16	57.68	55.05	0.28	0.39	0.52	0.80	0.87	0.92
m = 15	1	13.81	9.45	7.48	4.80	4.40	4.09	0.78	0.86	0.90	0.95	0.96	0.95
	2	34.12	22.52	17.11	9.64	8.49	7.65	0.64	0.77	0.85	0.93	0.93	0.93
	3	63.01	41.08	30.72	15.99	13.72	12.06	0.50	0.67	0.77	0.92	0.93	0.92
	4	102.48	65.39	48.87	24.46	20.77	17.83	0.40	0.56	0.69	0.89	0.92	0.93
	5	150.61	95.44	70.82	34.51	28.58	24.50	0.31	0.48	0.63	0.87	0.91	0.92

Scenario 2: $T_{expected}$ at 6 months

	Time Point (in month)	Median Precision at V(λ) = 0.1	0.5	1	5	10	50	Correct Coverage at V(λ) = 0.1	0.5	1	5	10	50
Prior	1	2.27	2.30	2.27	2.29	2.38	2.68	0.97	0.97	0.97	0.97	0.98	0.99
	2	5.61	5.55	5.47	5.66	5.83	6.66	0.93	0.93	0.93	0.94	0.95	0.97
	3	9.25	9.29	9.37	9.56	9.80	11.36	0.91	0.92	0.93	0.93	0.93	0.96
	4	14.09	14.08	14.16	14.41	14.62	16.26	0.90	0.90	0.91	0.91	0.92	0.95
	5	19.64	19.61	19.58	19.80	20.03	23.12	0.88	0.87	0.88	0.89	0.90	0.95
m = 3	1	3.80	3.75	3.80	4.00	4.24	6.18	0.95	0.95	0.95	0.96	0.96	0.96
	2	7.18	7.16	7.15	7.53	8.20	13.11	0.93	0.93	0.94	0.95	0.96	0.96
	3	11.58	11.51	11.47	12.13	13.42	23.05	0.92	0.92	0.93	0.96	0.96	0.97
	4	16.63	16.78	16.71	17.86	19.96	35.86	0.90	0.91	0.92	0.94	0.96	0.96
	5	22.90	22.94	22.98	24.61	27.93	51.49	0.88	0.88	0.89	0.95	0.97	0.96
m = 4	1	4.02	3.92	3.98	4.04	4.36	5.99	0.95	0.95	0.95	0.96	0.95	0.95
	2	7.20	7.16	7.10	7.49	8.26	12.71	0.93	0.94	0.94	0.96	0.96	0.96
	3	11.82	11.73	11.71	12.23	13.67	22.14	0.90	0.91	0.92	0.95	0.95	0.95
	4	17.03	16.93	16.92	18.10	20.38	34.62	0.89	0.91	0.91	0.95	0.96	0.95
	5	23.23	23.02	22.96	24.45	28.16	49.11	0.87	0.89	0.90	0.95	0.96	0.95
m = 5	1	3.82	3.81	3.78	3.86	4.17	5.54	0.96	0.96	0.96	0.97	0.97	0.96
	2	7.19	7.10	7.08	7.27	8.07	11.45	0.93	0.93	0.94	0.96	0.96	0.96
	3	11.82	11.67	11.45	11.99	13.37	20.18	0.91	0.92	0.93	0.96	0.96	0.95
	4	16.92	16.70	16.62	17.44	19.30	30.65	0.89	0.90	0.91	0.94	0.96	0.95
	5	24.05	23.61	23.35	24.79	27.72	44.58	0.86	0.88	0.89	0.93	0.95	0.94
m = 6	1	3.77	3.75	3.75	3.75	3.94	4.94	0.95	0.96	0.96	0.96	0.96	0.96
	2	7.30	7.26	7.15	7.32	7.72	10.30	0.93	0.93	0.94	0.95	0.96	0.95
	3	12.01	11.80	11.69	12.09	12.88	18.06	0.91	0.92	0.92	0.95	0.95	0.94
	4	17.52	17.36	17.08	17.29	18.77	26.97	0.88	0.90	0.91	0.94	0.96	0.95
	5	23.63	23.29	23.04	23.54	25.79	38.14	0.87	0.88	0.88	0.93	0.94	0.94
m = 7	1	3.81	3.72	3.70	3.66	3.81	4.52	0.95	0.95	0.96	0.97	0.97	0.96
	2	7.47	7.29	7.17	7.24	7.62	9.73	0.93	0.93	0.95	0.96	0.95	0.95
	3	12.14	11.83	11.72	11.64	12.40	16.73	0.91	0.92	0.93	0.94	0.95	0.94
	4	17.37	16.96	16.89	16.64	17.80	24.26	0.88	0.89	0.91	0.94	0.94	0.93
	5	23.25	22.83	22.50	22.68	24.63	34.28	0.86	0.88	0.90	0.94	0.95	0.94
m = 15	1	3.94	3.86	3.76	3.68	3.70	3.78	0.95	0.95	0.95	0.96	0.96	0.95
	2	7.29	7.09	6.88	6.52	6.60	6.91	0.92	0.93	0.94	0.94	0.94	0.94
	3	11.76	11.26	10.80	9.84	9.81	10.63	0.91	0.92	0.93	0.95	0.95	0.93
	4	17.32	16.59	15.74	14.35	14.39	15.48	0.87	0.88	0.90	0.92	0.93	0.93
	5	23.31	22.01	21.09	18.98	19.22	21.00	0.86	0.88	0.90	0.92	0.93	0.93

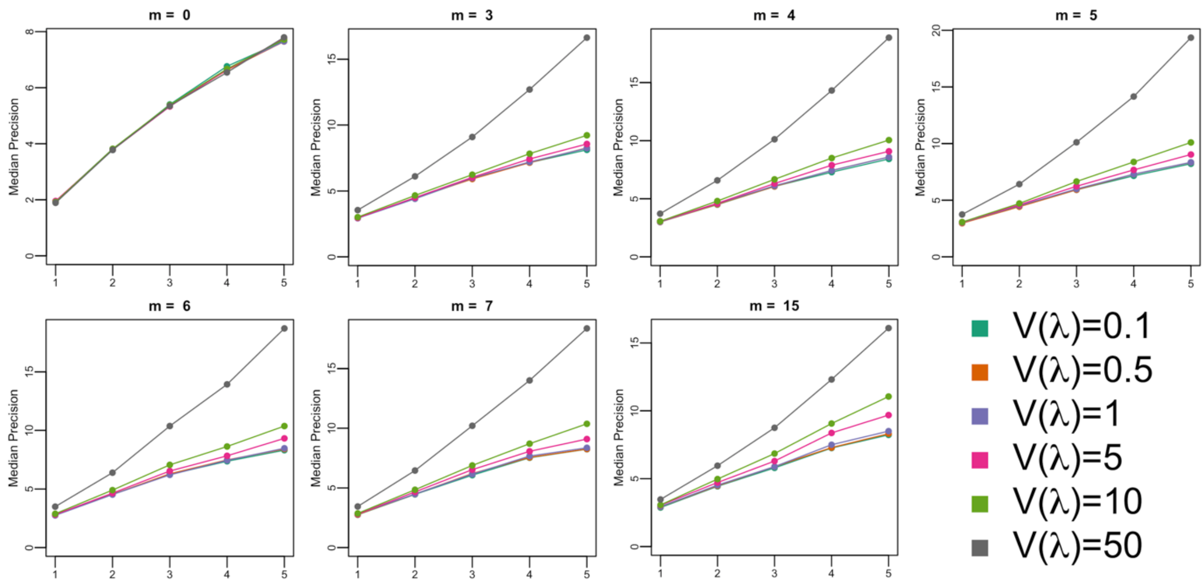
Scenario 3: $T_{expected}$ at 3 months

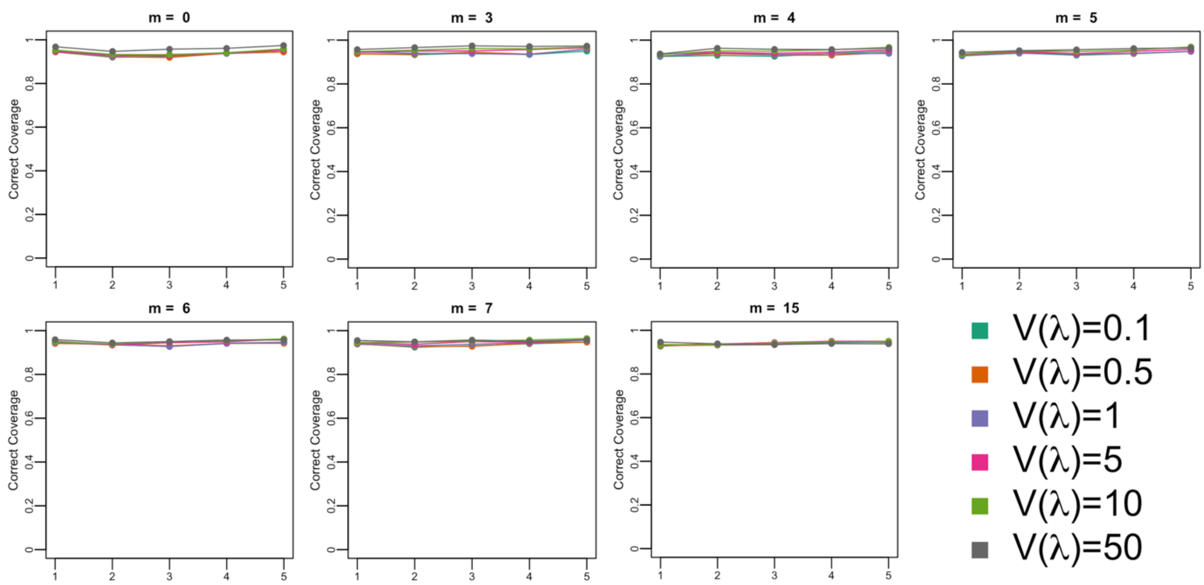




	Time Point (in month)	Median Precision at V(λ) = 0.1	0.5	1	5	10	50	Correct Coverage at V(λ) = 0.1	0.5	1	5	10	50
Prior	1	1.94	1.95	1.92	1.96	2.00	2.08	0.97	0.97	0.97	0.97	0.97	0.98
	2	4.03	4.02	4.02	4.00	3.99	4.30	0.94	0.95	0.94	0.95	0.96	0.97
	3	5.90	5.91	5.94	5.94	6.04	6.44	0.95	0.95	0.94	0.95	0.96	0.97
	4	7.68	7.71	7.73	7.82	7.82	8.42	0.94	0.95	0.95	0.95	0.96	0.97
	5	9.34	9.48	9.45	9.49	9.62	10.63	0.94	0.95	0.95	0.96	0.96	0.98
m = 3	1	3.00	3.01	3.01	3.11	3.23	4.43	0.94	0.95	0.94	0.95	0.96	0.96
	2	4.76	4.83	4.79	5.05	5.38	8.51	0.96	0.95	0.96	0.97	0.97	0.97
	3	6.69	6.71	6.77	7.26	7.87	13.81	0.95	0.94	0.95	0.96	0.96	0.97
	4	8.50	8.51	8.57	9.41	10.57	20.79	0.95	0.96	0.96	0.97	0.98	0.97
	5	10.48	10.56	10.79	11.84	13.65	28.82	0.96	0.96	0.96	0.97	0.97	0.98
m = 4	1	3.09	3.09	3.10	3.26	3.39	4.57	0.94	0.94	0.94	0.94	0.95	0.95
	2	4.77	4.83	4.81	5.13	5.59	8.69	0.95	0.95	0.95	0.96	0.96	0.96
	3	6.82	6.88	6.90	7.60	8.29	14.28	0.95	0.95	0.95	0.96	0.96	0.96
	4	8.79	8.84	8.95	10.06	11.51	21.92	0.95	0.95	0.96	0.95	0.96	0.96
	5	10.76	10.90	11.02	12.53	14.56	30.06	0.95	0.95	0.96	0.97	0.97	0.96
m = 5	1	3.06	3.02	3.03	3.17	3.40	4.41	0.96	0.95	0.96	0.96	0.97	0.96
	2	4.88	4.81	4.86	5.22	5.59	8.38	0.96	0.95	0.95	0.96	0.96	0.96
	3	6.84	6.86	6.88	7.54	8.47	14.13	0.96	0.95	0.96	0.96	0.96	0.96
	4	8.61	8.68	8.73	9.87	11.21	20.54	0.96	0.96	0.96	0.97	0.97	0.96
	5	10.93	10.91	11.29	12.68	14.94	29.26	0.96	0.96	0.96	0.97	0.96	0.96
m = 6	1	2.85	2.90	2.94	3.00	3.23	4.03	0.95	0.96	0.96	0.96	0.97	0.96
	2	4.87	4.92	4.89	5.23	5.68	7.89	0.95	0.94	0.95	0.96	0.95	0.95
	3	7.06	7.15	7.26	7.82	8.71	13.48	0.95	0.94	0.94	0.96	0.96	0.95
	4	9.06	9.10	9.15	10.05	11.43	19.37	0.96	0.96	0.96	0.96	0.97	0.96
	5	11.02	11.02	11.16	12.84	14.94	26.57	0.95	0.96	0.96	0.97	0.97	0.95
m = 7	1	2.92	2.84	2.91	3.00	3.18	3.85	0.95	0.96	0.96	0.96	0.96	0.96
	2	4.89	4.92	4.94	5.29	5.67	7.85	0.95	0.94	0.95	0.96	0.96	0.96
	3	7.09	7.13	7.23	7.64	8.60	12.82	0.95	0.95	0.95	0.95	0.96	0.95
	4	9.02	9.18	9.11	10.11	11.58	18.49	0.95	0.95	0.96	0.96	0.96	0.95
	5	10.74	10.72	10.94	12.54	14.67	25.20	0.95	0.96	0.96	0.97	0.97	0.96
m = 15	1	3.04	3.07	3.00	3.20	3.36	3.60	0.96	0.96	0.96	0.96	0.95	0.95
	2	4.87	4.86	4.91	5.18	5.43	6.47	0.94	0.95	0.95	0.94	0.94	0.94
	3	6.71	6.79	6.80	7.40	8.04	9.63	0.96	0.95	0.96	0.96	0.95	0.94
	4	8.82	8.98	9.02	10.12	11.04	14.02	0.95	0.94	0.95	0.95	0.94	0.93
	5	10.72	10.78	10.99	12.54	14.09	18.47	0.94	0.95	0.95	0.95	0.95	0.94

Scenario 4: $T_{expected}$ at 0 months





	Time Point (in month)	Median Precision at V(λ) = 0.1	0.5	1	5	10	50	Correct Coverage at V(λ) = 0.1	0.5	1	5	10	50
	1	1.95	1.95	1.94	1.96	1.92	1.89	0.94	0.95	0.95	0.95	0.95	0.97
	2	3.78	3.81	3.82	3.78	3.82	3.78	0.92	0.92	0.92	0.93	0.93	0.95
Prior	3	5.40	5.36	5.34	5.33	5.38	5.35	0.92	0.92	0.93	0.93	0.93	0.96
	4	6.76	6.63	6.67	6.64	6.67	6.54	0.94	0.94	0.94	0.94	0.94	0.96
	5	7.67	7.65	7.66	7.75	7.72	7.80	0.94	0.94	0.95	0.95	0.96	0.97
	1	2.94	2.96	2.93	2.96	3.01	3.54	0.94	0.94	0.95	0.94	0.95	0.96
	2	4.41	4.47	4.41	4.50	4.66	6.11	0.93	0.94	0.94	0.95	0.95	0.97
m = 3	3	5.95	5.91	5.99	6.04	6.24	9.10	0.94	0.94	0.94	0.95	0.96	0.97
	4	7.15	7.15	7.20	7.43	7.83	12.70	0.93	0.94	0.94	0.96	0.96	0.97
	5	8.12	8.27	8.24	8.56	9.22	16.64	0.95	0.96	0.96	0.96	0.97	0.97
	1	3.01	2.99	3.01	3.06	3.06	3.71	0.92	0.93	0.93	0.94	0.93	0.94
	2	4.50	4.53	4.58	4.61	4.80	6.58	0.93	0.94	0.94	0.94	0.95	0.96
m = 4	3	6.06	6.07	6.12	6.31	6.67	10.12	0.93	0.93	0.93	0.94	0.95	0.96
	4	7.29	7.44	7.43	7.89	8.50	14.32	0.94	0.93	0.94	0.94	0.96	0.96
	5	8.43	8.59	8.59	9.08	10.05	18.87	0.95	0.94	0.94	0.96	0.97	0.96
	1	2.98	2.97	3.03	3.06	3.07	3.74	0.93	0.93	0.93	0.94	0.94	0.94
	2	4.43	4.43	4.51	4.59	4.71	6.41	0.94	0.95	0.94	0.95	0.95	0.95
m = 5	3	5.92	5.92	5.99	6.23	6.65	10.11	0.93	0.94	0.94	0.94	0.95	0.96
	4	7.15	7.29	7.30	7.67	8.37	14.15	0.94	0.94	0.94	0.95	0.96	0.96
	5	8.21	8.33	8.34	9.03	10.10	19.34	0.95	0.95	0.95	0.96	0.97	0.96
	1	2.79	2.77	2.75	2.81	2.88	3.49	0.94	0.94	0.95	0.95	0.95	0.96
	2	4.55	4.54	4.53	4.65	4.91	6.39	0.94	0.94	0.94	0.93	0.94	0.94
m = 6	3	6.24	6.29	6.21	6.53	7.06	10.37	0.93	0.93	0.93	0.94	0.95	0.95
	4	7.37	7.48	7.45	7.83	8.63	13.93	0.94	0.94	0.94	0.95	0.95	0.96
	5	8.31	8.41	8.48	9.32	10.37	18.71	0.94	0.94	0.95	0.96	0.96	0.96
	1	2.75	2.77	2.82	2.80	2.86	3.44	0.94	0.94	0.94	0.94	0.95	0.96
	2	4.46	4.49	4.49	4.66	4.85	6.46	0.92	0.93	0.93	0.94	0.95	0.95
m = 7	3	6.07	6.20	6.16	6.53	6.88	10.21	0.93	0.93	0.94	0.95	0.95	0.96
	4	7.53	7.56	7.67	8.07	8.70	14.01	0.94	0.94	0.94	0.95	0.96	0.95
	5	8.24	8.26	8.36	9.09	10.37	18.37	0.95	0.95	0.96	0.96	0.96	0.96
	1	2.87	2.93	2.94	3.04	3.06	3.47	0.93	0.93	0.94	0.93	0.93	0.95
	2	4.44	4.48	4.52	4.71	4.97	5.96	0.94	0.93	0.93	0.94	0.93	0.94
m = 15	3	5.79	5.89	5.89	6.30	6.85	8.75	0.93	0.93	0.94	0.94	0.94	0.94
	4	7.25	7.29	7.50	8.37	9.06	12.30	0.94	0.95	0.94	0.95	0.95	0.94
	5	8.22	8.31	8.50	9.68	11.05	16.09	0.95	0.94	0.95	0.95	0.95	0.94

UNIVERSITÉ CATHOLIQUE DE LOUVAIN
Faculté des sciences
Place des sciences, 2 bte L6.06.01, 1348 Louvain-la-Neuve, Belgique | **www.uclouvain.be/sc**