Markov Sick-Sicker model in R

With simulation-time dependency

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This Code adaptation Developed by the Decision Analysis in R for Technologies in Health (DARTH) workgroup.

This code implements a simulation-time-dependent Sick-Sicker cSTM model to conduct a CEA of two strategies: - Standard of Care (SoC): best available care for the patients with the disease. This scenario reflects the natural history of the disease
progression. - Strategy AB: This strategy combines treatment A and treatment B. The disease progression is reduced, and individuals in the Sick state have an
improved quality of life.

Change `eval` to `TRUE` if you want to knit this document.

```
rm(list = ls())      # clear memory (removes all the variables from the workspace)
```

01 Load packages

```
if (!require('pacman')) install.packages('pacman'); library(pacman) # use this package to conveniently
# load (install if required) packages from CRAN
p_load("dplyr", "tidyr", "reshape2", "devtools", "scales", "ellipse", "ggplot2", "lazyeval", "igraph",
# load (install if required) packages from GitHub
# install_github("DARTH-git/darthtools", force = TRUE) #Uncomment if there is a newer version
p_load_gh("DARTH-git/darthtools")
```

02 Load functions

```
# all functions are in the darthtools package
```

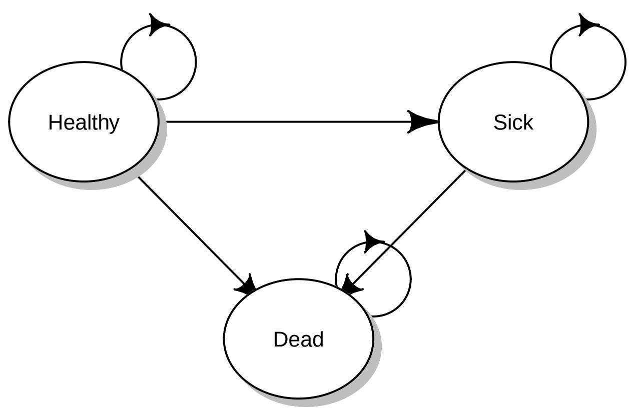
03 Model input

```
## General setup
cycle_length    <- 1                              # cycle length equal to monthly
n_cycles        <- 120                             # number of cycles
v_names_cycles  <- paste("cycle", 0:n_cycles)     # cycle names
v_names_states  <- c("Healthy", "Sick", "Dead")   # state names
n_states        <- length(v_names_states)         # number of health states

### Discounting factors

annual_rate <- 0.3
d_c <- 0.3  # annual discount rate for costs
d_e <- 0.3  # annual discount rate for QALYs


### Strategies
v_names_str     <- c("Treatment A",
                     "Treatment B")
n_str           <- length(v_names_str)            # number of strategies

## Within-cycle correction (WCC) using Simpson's 1/3 rule
v_wcc <- gen_wcc(n_cycles = n_cycles,  method = "Simpson1/3")

### Transition probabilities


### State rewards
#### Costs
c_H       <- 400   # cost of one cycle in healthy state
c_S       <- 1000  # cost of one cycle in sick state
c_D       <- 0     # cost of one cycle in dead state
c_trtA    <- 800   # cost of treatment A (per cycle) in healthy state
c_trtB    <- 1500  # cost of treatment B (per cycle) in healthy state
```

```r
#### Utilities
u_H       <- 1     # one year utility when healthy
u_S       <- 0.5   # one year utility when sick
u_D       <- 0     # one year utility when dead


### Discount weight for costs and effects
v_dwc     <- 1 / ((1 + (((1 + d_c)^(1/12) - 1) * cycle_length)) ^ (0:n_cycles))
v_dwe     <- 1 / ((1 + (((1 + d_e)^(1/12) - 1) * cycle_length)) ^ (0:n_cycles))
```

04 Construct state-transition models

```r
m_P_diag <- matrix(0, nrow = n_states, ncol = n_states, dimnames = list(v_names_states, v_names_states))
m_P_diag["Healthy", "Sick" ]      = ""
m_P_diag["Healthy", "Dead" ]      = ""
m_P_diag["Healthy", "Healthy" ]  = ""
m_P_diag["Sick"    , "Dead" ]     = ""
m_P_diag["Sick"    , "Sick" ]     = ""
m_P_diag["Dead"    , "Dead" ]     = ""
layout.fig <- c(2, 1)
plotmat(t(m_P_diag), t(layout.fig), self.cex = 0.5, curve = 0, arr.pos = 0.8,
        latex = T, arr.type = "curved", relsize = 0.85, box.prop = 0.8,
        cex = 0.8, box.cex = 0.7, lwd = 1)
```



04.1 Initial state vector

```r
# All starting healthy
v_m_init <- c("Healthy" = 1, "Sick" = 0, "Dead" = 0)
v_m_init
```

```
## Healthy    Sick    Dead
##       1       0       0
```

04.2 Initialize cohort traces

```r
### Initialize cohort trace for trtB
m_M_trtB <- matrix(0,
                   nrow = (n_cycles + 1), ncol = n_states,
                   dimnames = list(v_names_cycles, v_names_states))
# Store the initial state vector in the first row of the cohort trace
m_M_trtB[1, ] <- v_m_init

## Initialize cohort traces for treatments A and B
# Structure and initial states are the same as for SoC
m_M_trtA <- m_M_trtB
```

04.3.1 Create transition probability arrays

```r
p_trtA<- read.csv("M.trA.csv",header = TRUE, nrows = 121)
p_trtB<- read.csv("M.trB.csv",header = TRUE, nrows = 121)
m_M_trtA<- as.matrix(p_trtA)
m_M_trtB<- as.matrix(p_trtB)
rownames(m_M_trtA) <- v_names_cycles
colnames(m_M_trtA) <- v_names_states
rownames(m_M_trtB) <- v_names_cycles
colnames(m_M_trtB) <- v_names_states
## Store the cohort traces in a list
l_m_M <- list(A   =  m_M_trtA,
              B   =  m_M_trtB)
names(l_m_M) <- v_names_str
```

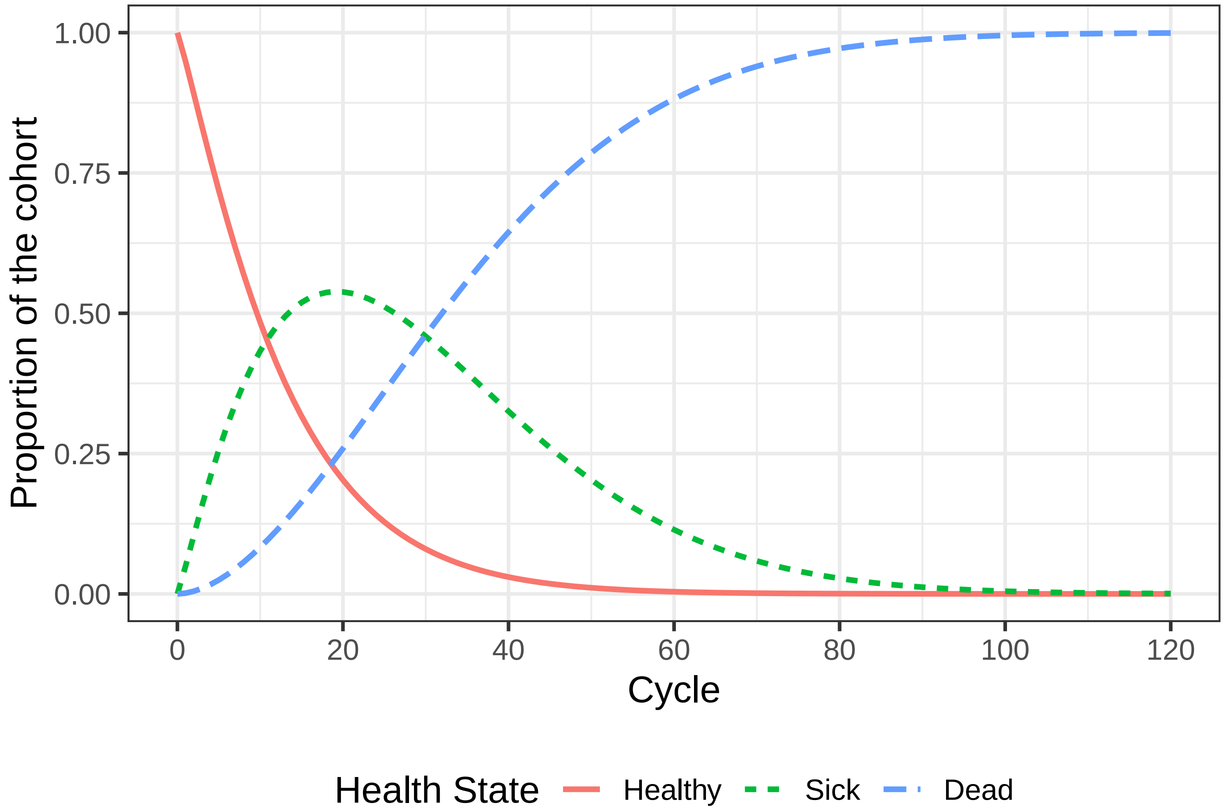
04.3 Create transition probability arrays

05 Run Markov model

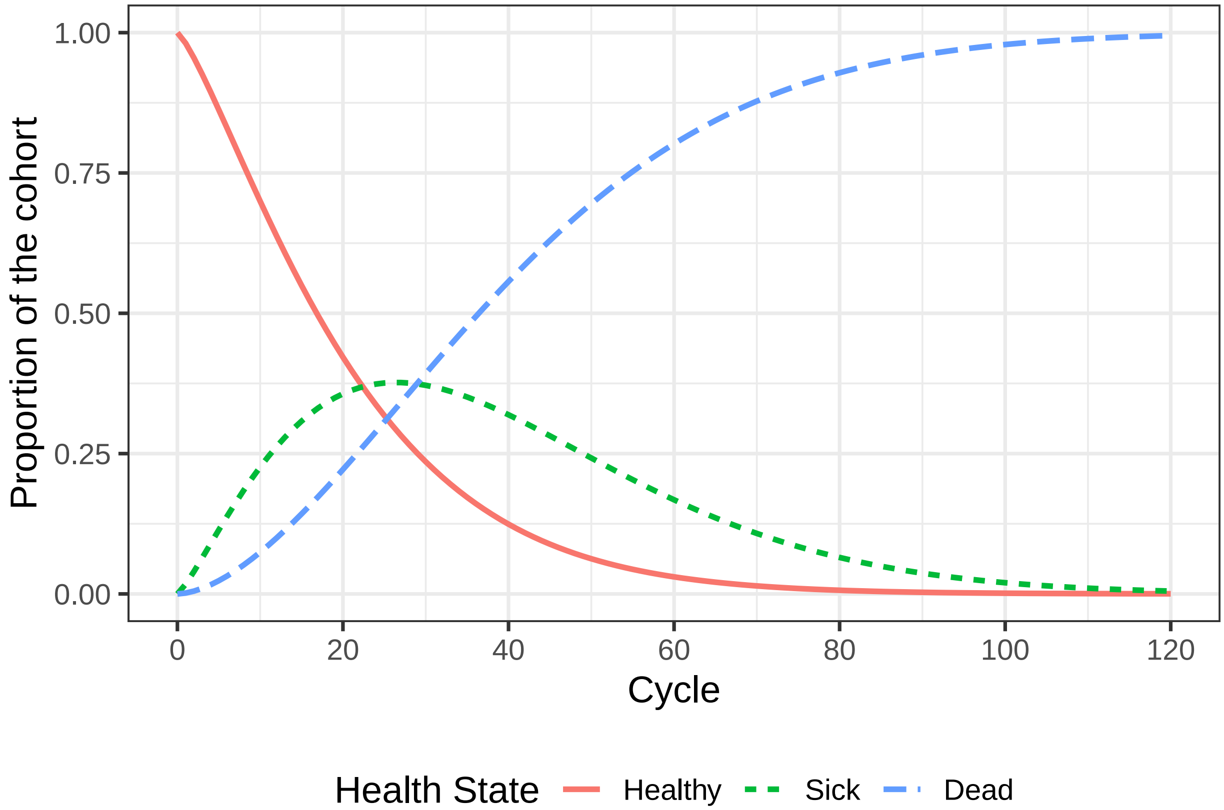
06 Plot Outputs

06.1 Plot the cohort trace for strategies SoC

```r
plot_trace(m_M_trtA)
```



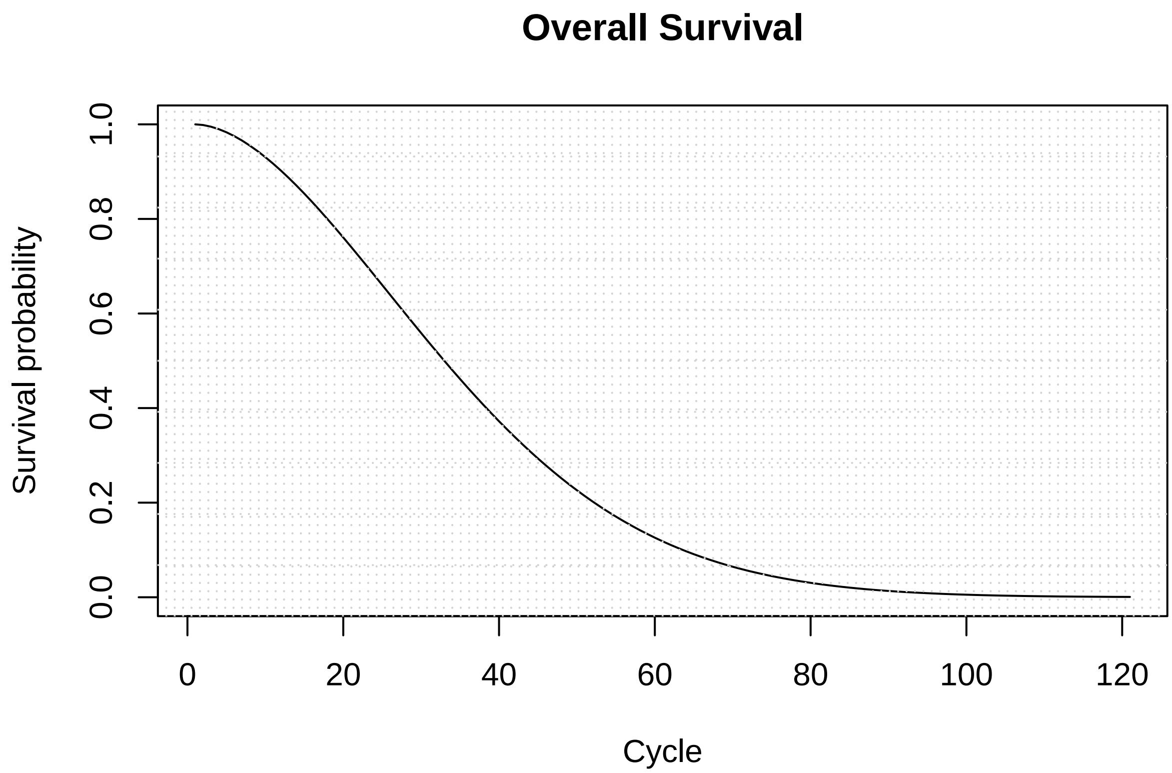

```
plot_trace( m_M_trtB)
```



06.2 Overall Survival (OS)

Print the overall survival for the Standard of Care

```
v_os_trtA <- 1 - m_M_trtA[, "Dead"]     # calculate the overall survival (OS) probability
v_os_trtA <- rowSums(m_M_trtA[, 1:2])  # alternative way of calculating the OS probability

plot(v_os_trtA, type = 'l',
     ylim = c(0, 1),
     ylab = "Survival probability",
     xlab = "Cycle",
     main = "Overall Survival")  # create a simple plot showing the OS

# add grid
grid(nx = n_cycles, ny = 10, col = "lightgray", lty = "dotted", lwd = par("lwd"),
     equilogs = TRUE)
```

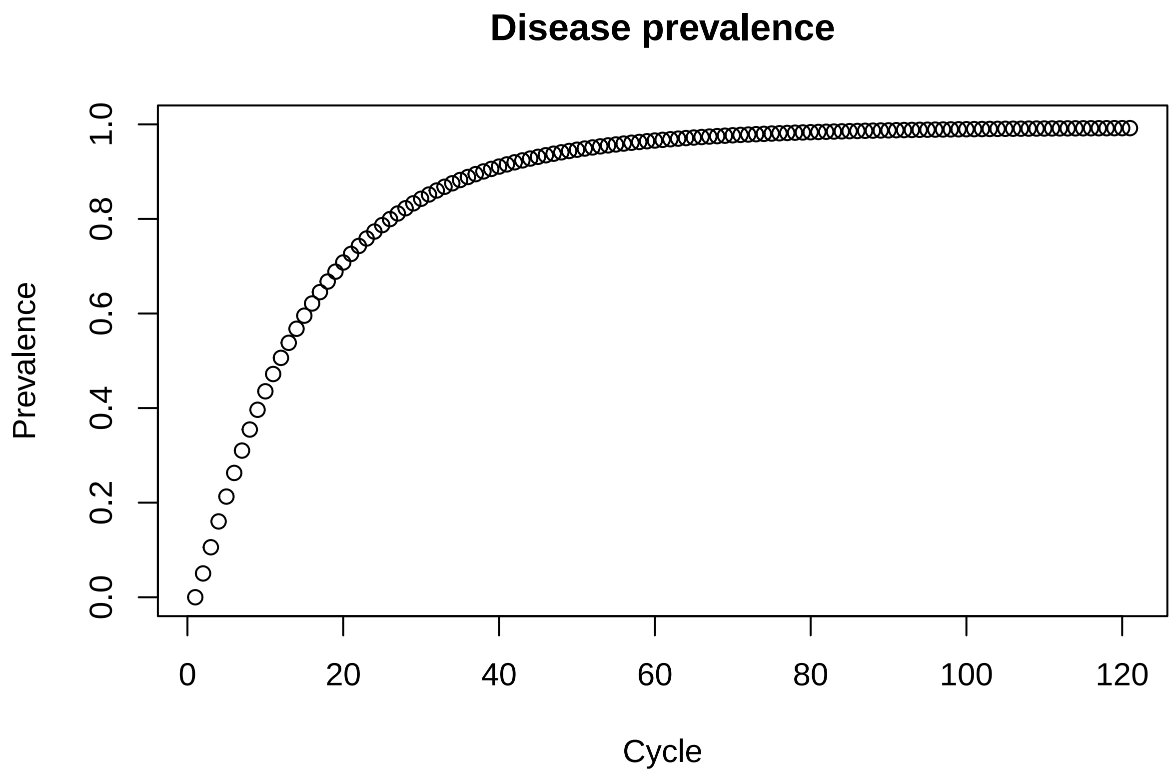


06.2.1 Life Expectancy (LE)

```
le_trtA <- sum(v_os_trtA)  # summing probability of OS over time  (i.e. life expectancy)
```

06.2.2 Disease prevalence

```
v_prev <- m_M_trtA[, "Sick"]/v_os_trtA
plot(v_prev,
     ylim = c(0, 1),
     ylab = "Prevalence",
     xlab = "Cycle",
     main = "Disease prevalence")
```



07 State Rewards

```r
## Scale by the cycle length
# Vector of state utilities under treatment A
v_u_trtA   <- c(H  = u_H/12,
                S  = u_S/12,
                D  = u_D/12) * cycle_length
# Vector of state costs under treatment A
v_c_trtA   <- c(H  = c_H + c_trtA,
                S  = c_S,
                D  = c_D) * cycle_length
# Vector of state utilities under treatment B
v_u_trtB   <- c(H  = u_H/12,
                S  = u_S/12,
                D  = u_D/12) * cycle_length
# Vector of state costs under treatment B
v_c_trtB   <- c(H  = c_H + c_trtB,
                S  = c_S,
                D  = c_D) * cycle_length

## Store state rewards
# Store the vectors of state utilities for each strategy in a list
l_u   <- list(A  = v_u_trtA,
              B  = v_u_trtB)
# Store the vectors of state cost for each strategy in a list
```

```r
l_c   <- list(A  = v_c_trtA,
              B  = v_c_trtB)

# assign strategy names to matching items in the lists
names(l_u) <- names(l_c) <- v_names_str
```

08 Compute expected outcomes

```r
# Create empty vectors to store total utilities and costs
v_tot_qaly <- v_tot_cost <- vector(mode = "numeric", length = n_str)
names(v_tot_qaly) <- names(v_tot_cost) <- v_names_str

## Loop through each strategy and calculate total utilities and costs
for (i in 1:n_str) {
  v_u_str <- l_u[[i]]   # select the vector of state utilities for the i-th strategy
  v_c_str <- l_c[[i]]   # select the vector of state costs for the i-th strategy

  ### Expected QALYs and costs per cycle
  ## Vector of QALYs and Costs
  # Apply state rewards
  v_qaly_str <- l_m_M[[i]] %*% v_u_str # sum the utilities of all states for each cycle
  v_cost_str <- l_m_M[[i]] %*% v_c_str # sum the costs of all states for each cycle

  ### Discounted total expected QALYs and Costs per strategy and apply within-cycle correction if appli
  # QALYs
  v_tot_qaly[i] <- t(v_qaly_str) %*% (v_dwe * v_wcc)
  # Costs
  v_tot_cost[i] <- t(v_cost_str) %*% (v_dwc * v_wcc)
}
```

09 Cost-effectiveness analysis (CEA)

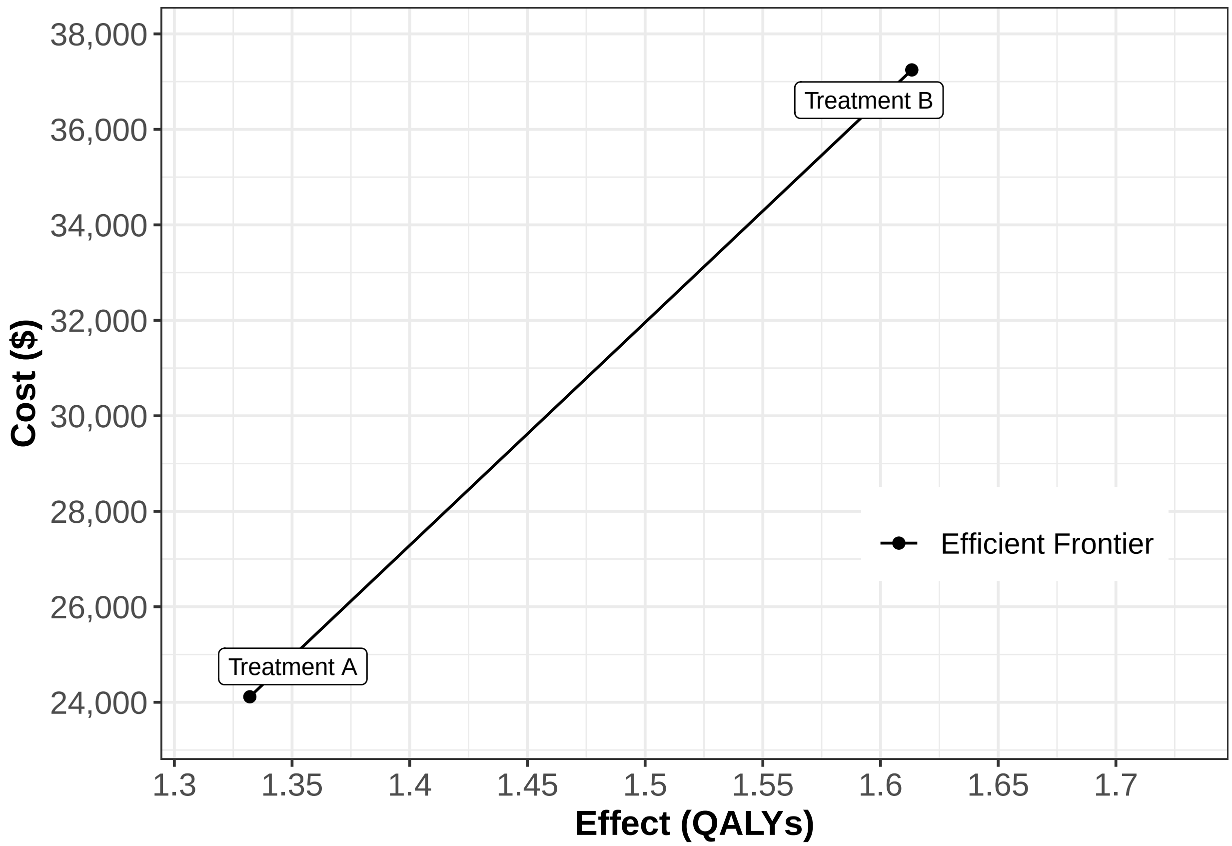
```r
## Incremental cost-effectiveness ratios (ICERs)
df_cea <- calculate_icers(cost       = v_tot_cost,
                          effect     = v_tot_qaly,
                          strategies = v_names_str)
df_cea
```

```
##                 Strategy     Cost   Effect Inc_Cost Inc_Effect     ICER Status
## Treatment A Treatment A 24114.83 1.332060       NA         NA       NA     ND
## Treatment B Treatment B 37244.76 1.613289 13129.93  0.2812287 46687.74     ND
```

```r
## CEA table in proper format
table_cea <- format_table_cea(df_cea)
table_cea
```

```
##                 Strategy Costs ($) QALYs Incremental Costs ($) Incremental QALYs
## Treatment A Treatment A    24,115  1.33                  <NA>                NA
## Treatment B Treatment B    37,245  1.61                13,130              0.28
##             ICER ($/QALY) Status
## Treatment A          <NA>     ND
## Treatment B        46,688     ND
```

```r
## CEA frontier
plot(df_cea, label = "all", txtsize = 14) +
  expand_limits(x = max(table_cea$QALYs) + 0.1) +
  theme(legend.position = c(0.8, 0.3))
```



10 Deterministic Sensitivity Analysis (DSA)

```r
## Load model, CEA and PSA functions
source('Functions_markov_3state_time1.R')
```

10.1 Model input for SA

```r
l_params_all <- list(
  # Transition probabilities
m_M_trtA,
m_M_trtB,
 ## State rewards
 # Costs
  c_H       = 400,   # cost of one cycle in healthy state
  c_S       = 1000,  # cost of one cycle in sick state
  c_D       = 0,     # cost of one cycle in dead state
  c_trtA    = 800,   # cost of treatment A (per cycle) in healthy state
  c_trtB    = 1500,  # cost of treatment B (per cycle) in healthy state
  # Utilities
```

```
  u_H       = 1,     # utility when healthy
  u_S       = 0.5,   # utility when sick
  u_D       = 0,     # utility when dead
  # Discount rates
  d_e       = 0.03,  # discount rate per cycle equal discount of costs and QALYs by 3%
  d_c       = 0.03,  # discount rate per cycle equal discount of costs and QALYs by 3%
  # Time horizon
  n_cycles  = 120     # simulation time horizon (number of cycles)
)
```

Test model functions

Two functions were defined in the `Functions_markov_3state_time.R` file. The first was the `decision_model()` function which takes in model parameters and outputs the Markov trace for all three strategies. The second is the `calculate_ce_out()` function which calls `decision_model()` and uses the resulting Markov trace to compute the total costs, QALYs, and net monetary benefit (NMB) for each strategy, returning a data frame of costs and QALYs.

```
# Try the decision_model() function
l_trace <- decision_model(l_params_all)
l_trace$m_M_trtA[1:5,]
```

```
## NULL
```

```
l_trace$a_P_trtA[,,1:3]
```

```
## NULL
```

```
# Try the calculate_ce_out() function
df_ce <- calculate_ce_out(l_params_all)
df_ce
```

```
##                Strategy     Cost   Effect      NMB
## Treatment A Treatment A 24114.83 1.332060 109091.2
## Treatment B Treatment B 37244.76 1.613289 124084.1
```

```
# Get strategies names (will be used to label plots)
v_names_str <- df_ce$Strategy
n_str <- length(v_names_str)
```

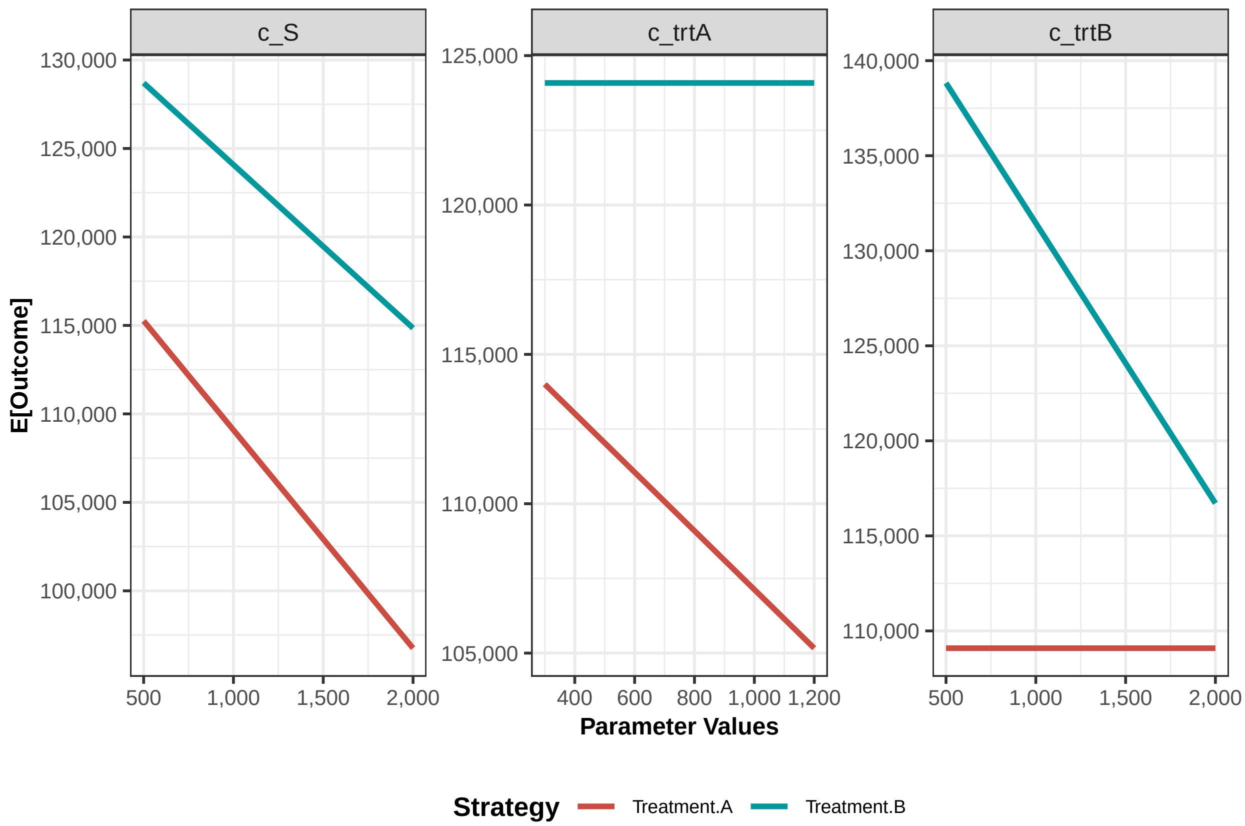
10.2 One-way sensitivity analysis (OWSA)

```
options(scipen = 999) # disabling scientific notation in R
# dataframe containing all parameters, their base case values, and the min and
# max values of the parameters of interest
df_params_owsa <- data.frame(pars = c("c_trtA", "c_trtB", "c_S"),
                             min  = c(300 , 500,   500),  # min parameter values
                             max  = c(1200, 2000, 2000)  # max parameter values
                             )
owsa_nmb  <- run_owsa_det(params_range     = df_params_owsa,    # dataframe with parameters for OWSA
                          params_basecase  = l_params_all,      # list with all parameters
                          nsamp            = 100,               # number of parameter values
                          FUN              = calculate_ce_out,  # function to compute outputs
                          outcomes         = c("NMB"),          # output to do the OWSA on
```

```
                              strategies       = v_names_str,       # names of the strategies
                              n_wtp            = 100000)              # extra argument to pass to FUN
```

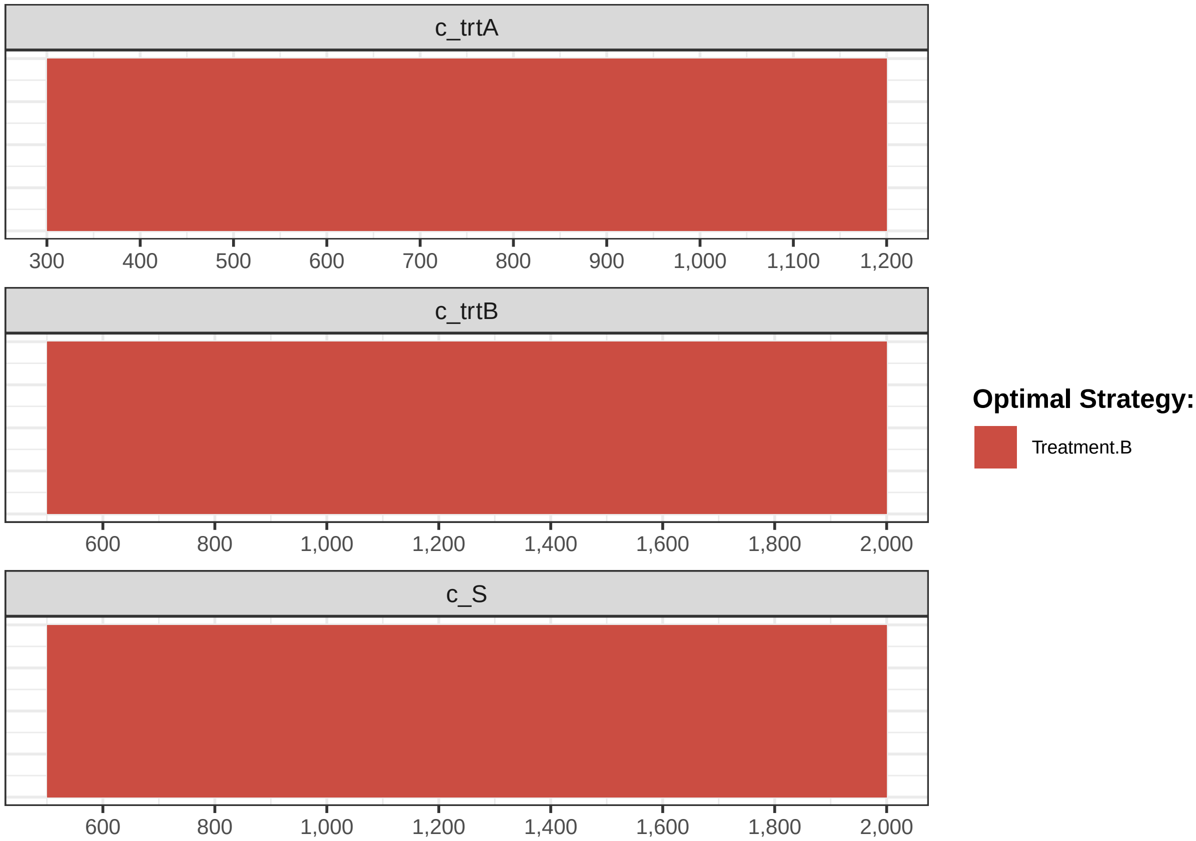
```
##   |                                                                                |
```

```
plot(owsa_nmb, txtsize = 10, n_x_ticks = 4,
     facet_scales = "free") +
     theme(legend.position = "bottom")
```



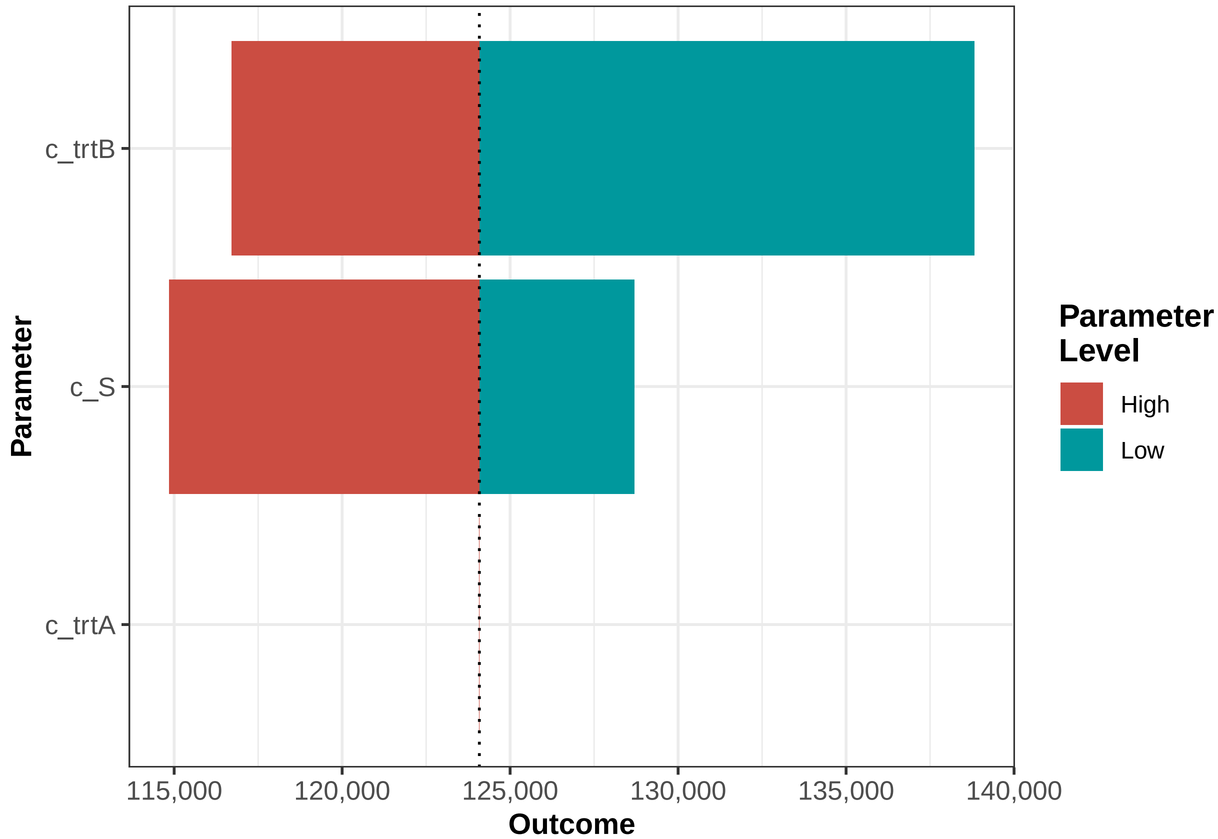
10.2.1 Optimal strategy with OWSA

```
owsa_opt_strat(owsa = owsa_nmb, txtsize = 10)
```



10.2.2 Tornado plot

```
owsa_tornado(owsa = owsa_nmb)
```

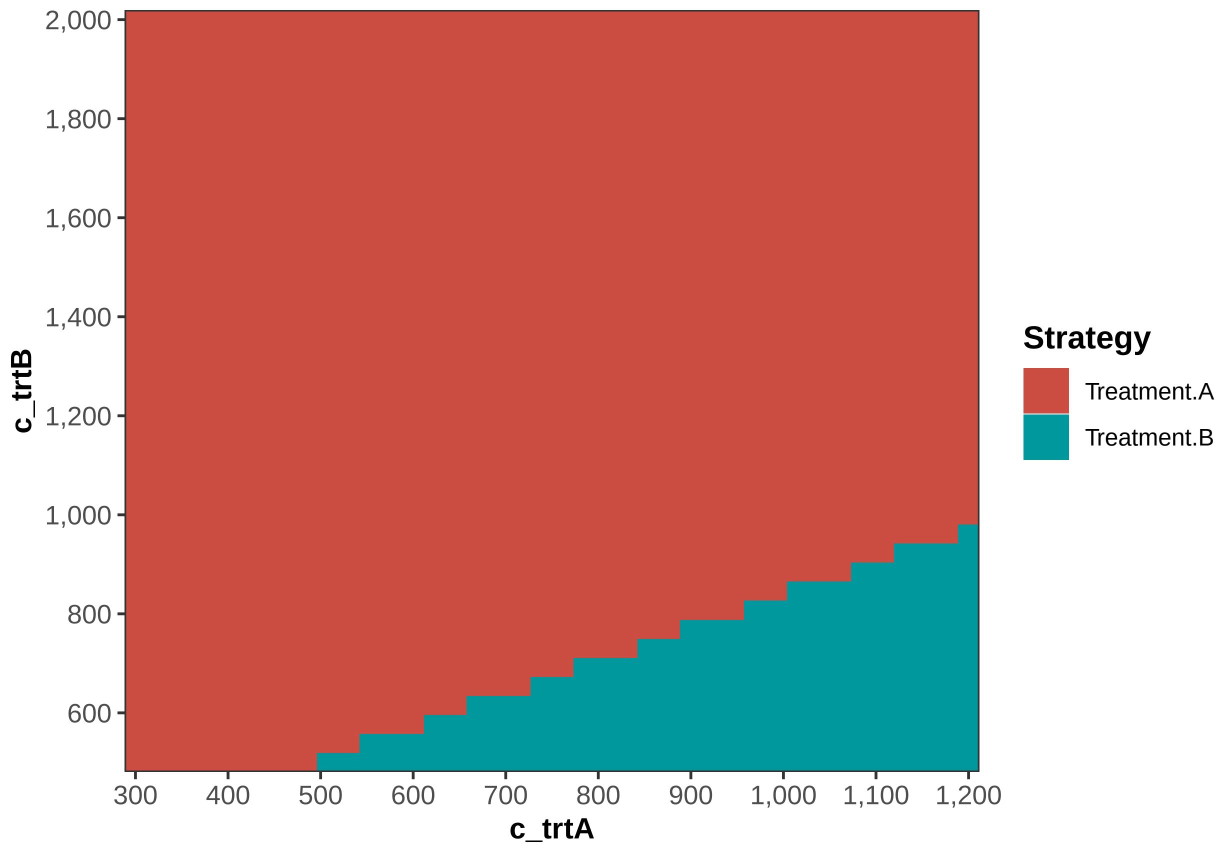


10.3 Two-way sensitivity analysis (TWSA)

```
# dataframe containing all parameters, their basecase values, and the min and
# max values of the parameters of interest
df_params_twsa <- data.frame(pars = c("c_trtA", "c_trtB"),
                             min  = c(300, 500),  # min parameter values
                             max  = c(1200, 2000) # max parameter values
                             )

twsa_nmb <- run_twsa_det(params_range    = df_params_twsa,    # dataframe with parameters for TWSA
                         params_basecase = l_params_all,      # list with all parameters
                         nsamp           = 40,                # number of parameter values
                         FUN             = calculate_ce_out,  # function to compute outputs
                         outcomes        = "NMB",             # output to do the TWSA on
                         strategies      = v_names_str,       # names of the strategies
                         n_wtp           = 5000)              # extra argument to pass to FUN
```

```
##   |                                                                              |
```

```
plot(twsa_nmb)
```



11 Probabilistic Sensitivity Analysis (PSA)

11.1 Model input

```
# Store the parameter names into a vector
v_names_params <- names(l_params_all)

## Test functions to generate CE outcomes and PSA dataset
# Test function to compute CE outcomes
calculate_ce_out(l_params_all)
```

```
##                Strategy     Cost   Effect      NMB
## Treatment A Treatment A 24114.83 1.332060 109091.2
## Treatment B Treatment B 37244.76 1.613289 124084.1
```

```
# Test function to generate PSA input dataset
generate_psa_params(10)
```

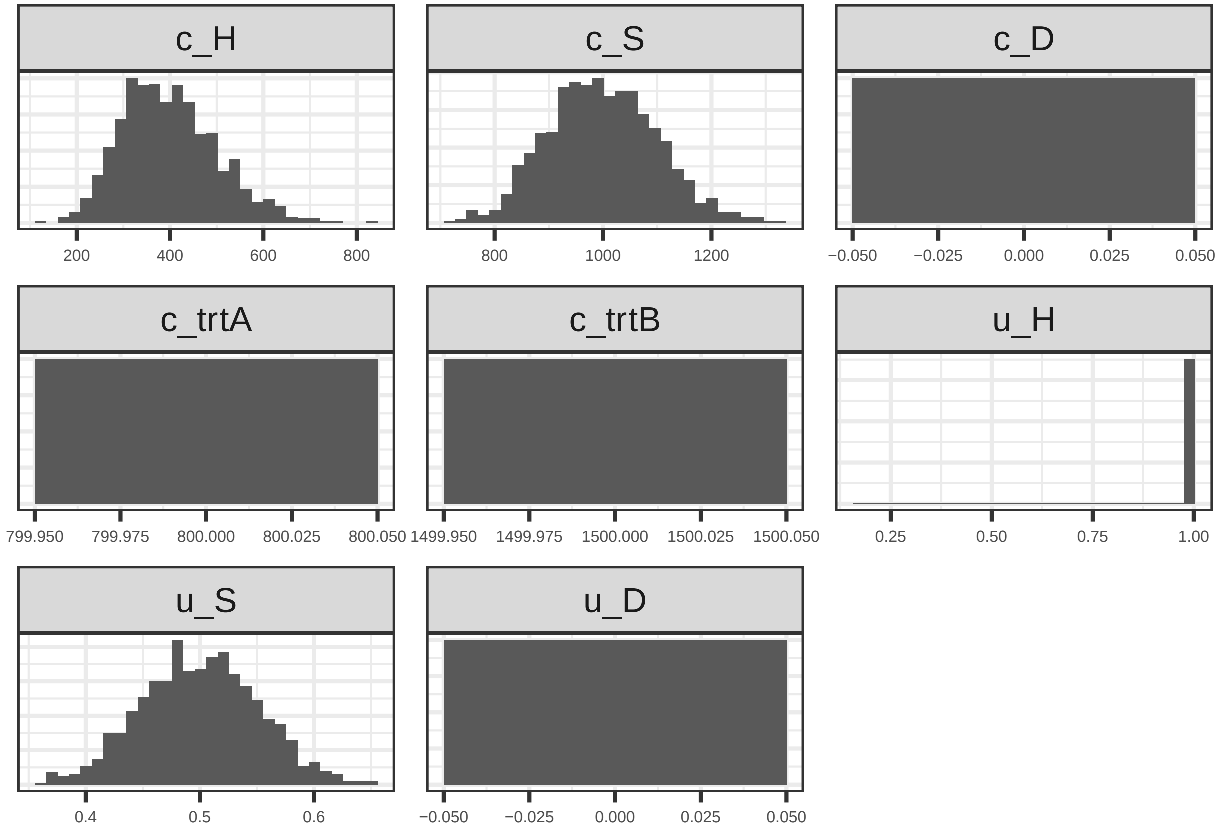
```
##         c_H       c_S c_D c_trtA c_trtB u_H       u_S u_D
## 1  537.2865  970.5874   0    800   1500   1 0.3847906   0
## 2  392.0464  917.3663   0    800   1500   1 0.4486215   0
## 3  304.0767  888.4998   0    800   1500   1 0.4974254   0
## 4  292.3548 1279.1368   0    800   1500   1 0.4678000   0
## 5  363.1699  975.7369   0    800   1500   1 0.5454105   0
## 6  376.5410 1032.3132   0    800   1500   1 0.4932370   0
## 7  324.4721  980.3957   0    800   1500   1 0.4933852   0
```

```
## 8  565.6859 1085.6563   0    800   1500   1 0.4774074   0
## 9  252.7441 1102.2173   0    800   1500   1 0.4283304   0
## 10 516.8618  905.9940   0    800   1500   1 0.5489382   0
```

```
## Generate PSA dataset
# Number of simulations
n_sim <- 1000

# Generate PSA input dataset
df_psa_input <- generate_psa_params(n_sim = n_sim)
# First six observations
head(df_psa_input)
```

```
##        c_H      c_S c_D c_trtA c_trtB u_H       u_S u_D
## 1 537.2865 1125.652   0    800   1500   1 0.5093511   0
## 2 392.0464 1104.588   0    800   1500   1 0.5025504   0
## 3 304.0767 1097.612   0    800   1500   1 0.4180469   0
## 4 292.3548 1133.857   0    800   1500   1 0.5667343   0
## 5 363.1699 1004.396   0    800   1500   1 0.4877285   0
## 6 376.5410 1087.334   0    800   1500   1 0.4692128   0
```

```
### Histogram of parameters
ggplot(melt(df_psa_input, variable.name = "Parameter"), aes(x = value)) +
  facet_wrap(~Parameter, scales = "free") +
  geom_histogram(aes(y = ..density..)) +
  ylab("") +
  theme_bw(base_size = 16) +
  theme(axis.text = element_text(size = 6),
        axis.title.x = element_blank(),
        axis.title.y = element_blank(),
        axis.text.y  = element_blank(),
        axis.ticks.y = element_blank())
```



11.2 Run PSA

```
# Initialize data.frames with PSA output
# data.frame of costs
df_c <- as.data.frame(matrix(0,
                             nrow = n_sim,
                             ncol = n_str))
colnames(df_c) <- v_names_str
# data.frame of effectiveness
df_e <- as.data.frame(matrix(0,
                             nrow = n_sim,
                             ncol = n_str))
colnames(df_e) <- v_names_str

# Conduct probabilistic sensitivity analysis
# Run Markov model on each parameter set of PSA input dataset
n_time_init_psa_series <- Sys.time()
for (i in 1:n_sim) { # i <- 1
  l_psa_input <- update_param_list(l_params_all, df_psa_input[i,])
  # Outcomes
  l_out_ce_temp  <- calculate_ce_out(l_psa_input)
  df_c[i, ]  <- l_out_ce_temp$Cost
  df_e[i, ]  <- l_out_ce_temp$Effect
  # Display simulation progress
  if (i/(n_sim/100) == round(i/(n_sim/100), 0)) { # display progress every 5%
```

```
    cat('\r', paste(i/n_sim * 100, "% done", sep = " "))
  }
}
```

```
##  1 % done 2 % done 3 % done 4 % done 5 % done 6 % done 7 % done 8 % done 9 % done 10 % done 11 % done
```

```
n_time_end_psa_series <- Sys.time()
n_time_total_psa_series <- n_time_end_psa_series - n_time_init_psa_series
print(paste0("PSA with ", scales::comma(n_sim), " simulations run in series in ",
             round(n_time_total_psa_series, 2), " ",
             units(n_time_total_psa_series)))
```

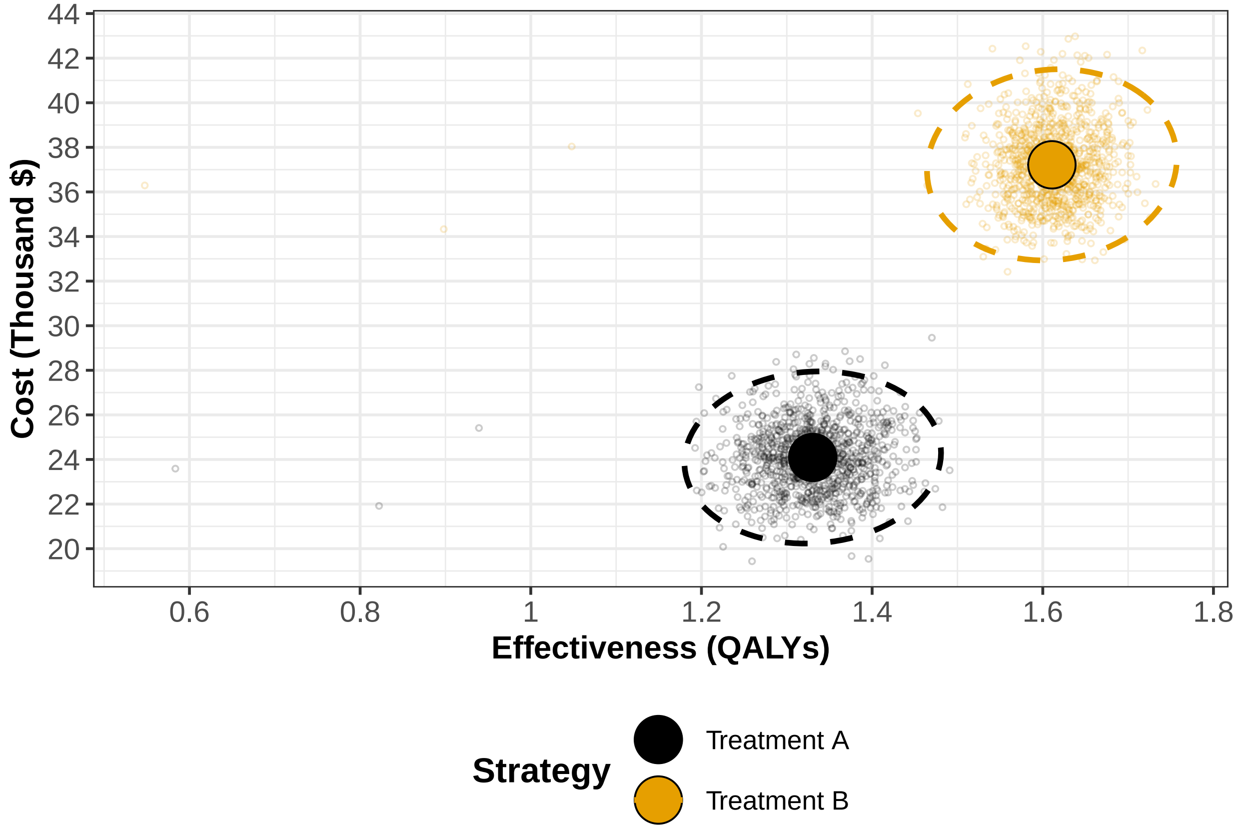
```
## [1] "PSA with 1,000 simulations run in series in 0.85 secs"
```

11.3 Visualize PSA results for CEA

```
### Create PSA object
l_psa <- make_psa_obj(cost          = df_c,
                      effectiveness = df_e,
                      parameters    = df_psa_input,
                      strategies    = v_names_str)
l_psa$strategies <- v_names_str
colnames(l_psa$effectiveness) <- v_names_str
colnames(l_psa$cost) <- v_names_str

# Vector with willingness-to-pay (WTP) thresholds.
v_wtp <- seq(0, 100000, by = 5000)
```

11.3.1 Cost-Effectiveness Scatter plot

```
### Cost-Effectiveness Scatter plot
txtsize <- 13
gg_scattter <- plot_psa(l_psa, txtsize = txtsize) +
  ggthemes::scale_color_colorblind() +
  ggthemes::scale_fill_colorblind() +
  scale_y_continuous("Cost (Thousand $)",
                     breaks = number_ticks(10),
                     labels = function(x) x/1000) +
  xlab("Effectiveness (QALYs)") +
  guides(col = guide_legend(nrow = 2)) +
  theme(legend.position = "bottom")
gg_scattter
```



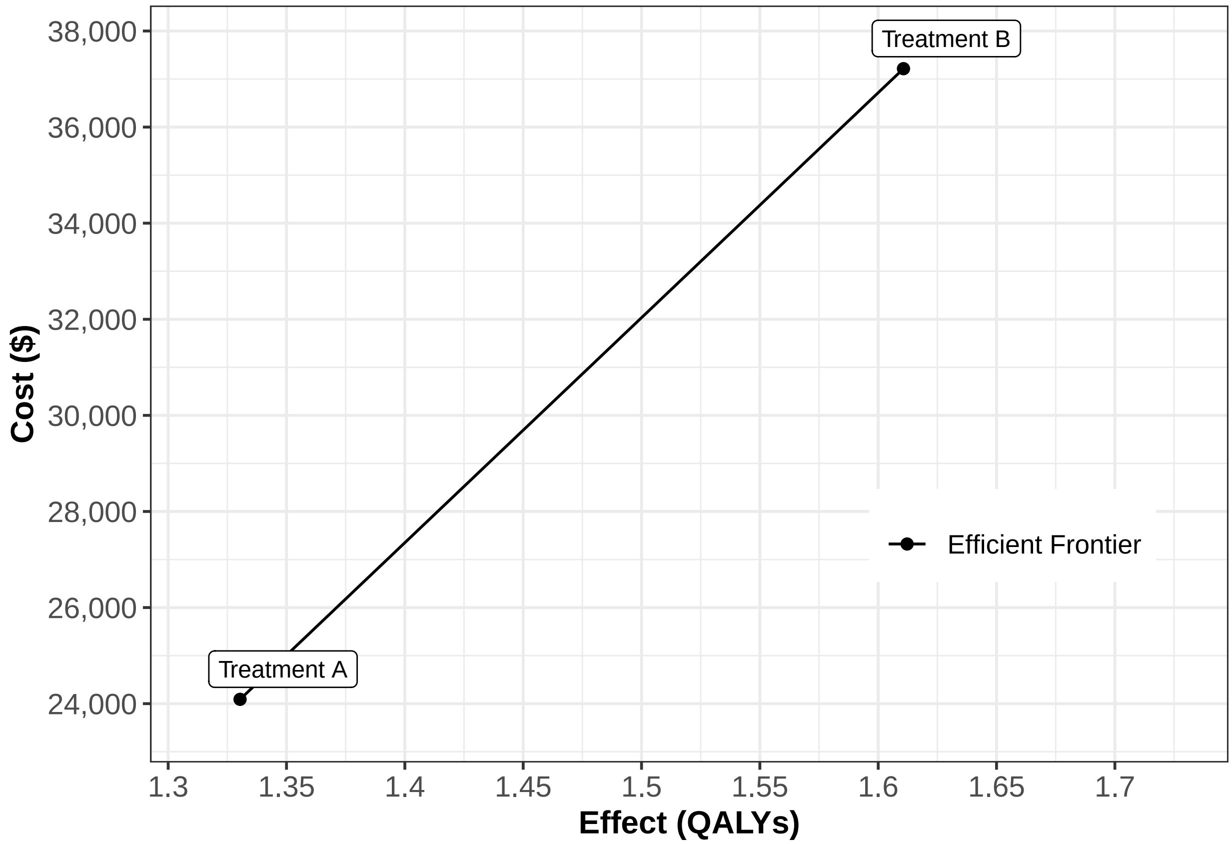
11.3.2 Incremental cost-effectiveness ratios (ICERs) with probabilistic output

```
### Incremental cost-effectiveness ratios (ICERs) with probabilistic output
# Compute expected costs and effects for each strategy from the PSA
df_out_ce_psa <- summary(l_psa)
df_cea_psa <- calculate_icers(cost       = df_out_ce_psa$meanCost,
                              effect     = df_out_ce_psa$meanEffect,
                              strategies = df_out_ce_psa$Strategy)
df_cea_psa
```

```
##      Strategy     Cost   Effect Inc_Cost Inc_Effect     ICER Status
## 1 Treatment A 24090.03 1.330379       NA         NA       NA     ND
## 2 Treatment B 37216.07 1.610679 13126.03  0.2803002 46828.49     ND
```

11.3.3 Plot cost-effectiveness frontier with probabilistic output

```
### Plot cost-effectiveness frontier with probabilistic output
plot_icers(df_cea_psa, label = "all", txtsize = txtsize) +
  expand_limits(x = max(table_cea$QALYs) + 0.1) +
  theme(legend.position = c(0.8, 0.3))
```

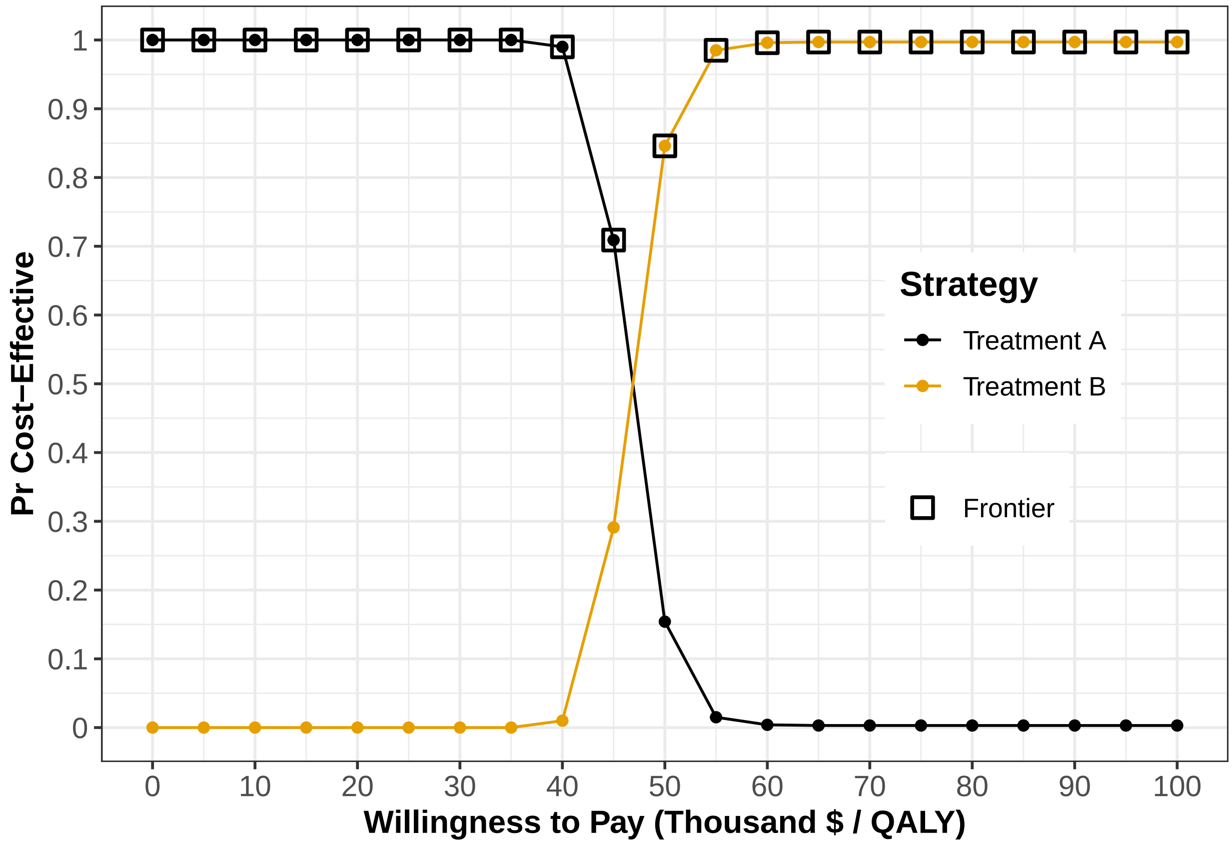


11.3.4 Cost-effectiveness acceptability curves (CEACs) and frontier (CEAF)

```
### Cost-effectiveness acceptability curves (CEACs) and frontier (CEAF)
ceac_obj <- ceac(wtp = v_wtp, psa = l_psa)
# Regions of highest probability of cost-effectiveness for each strategy
summary(ceac_obj)
```

```
##   range_min range_max cost_eff_strat
## 1         0     50000    Treatment A
## 2     50000    100000    Treatment B
```

```
# CEAC & CEAF plot
gg_ceac <- plot_ceac(ceac_obj, txtsize = txtsize, xlim = c(0, NA), n_x_ticks = 14) +
  ggthemes::scale_color_colorblind() +
  ggthemes::scale_fill_colorblind() +
  theme(legend.position = c(0.8, 0.48))
gg_ceac
```



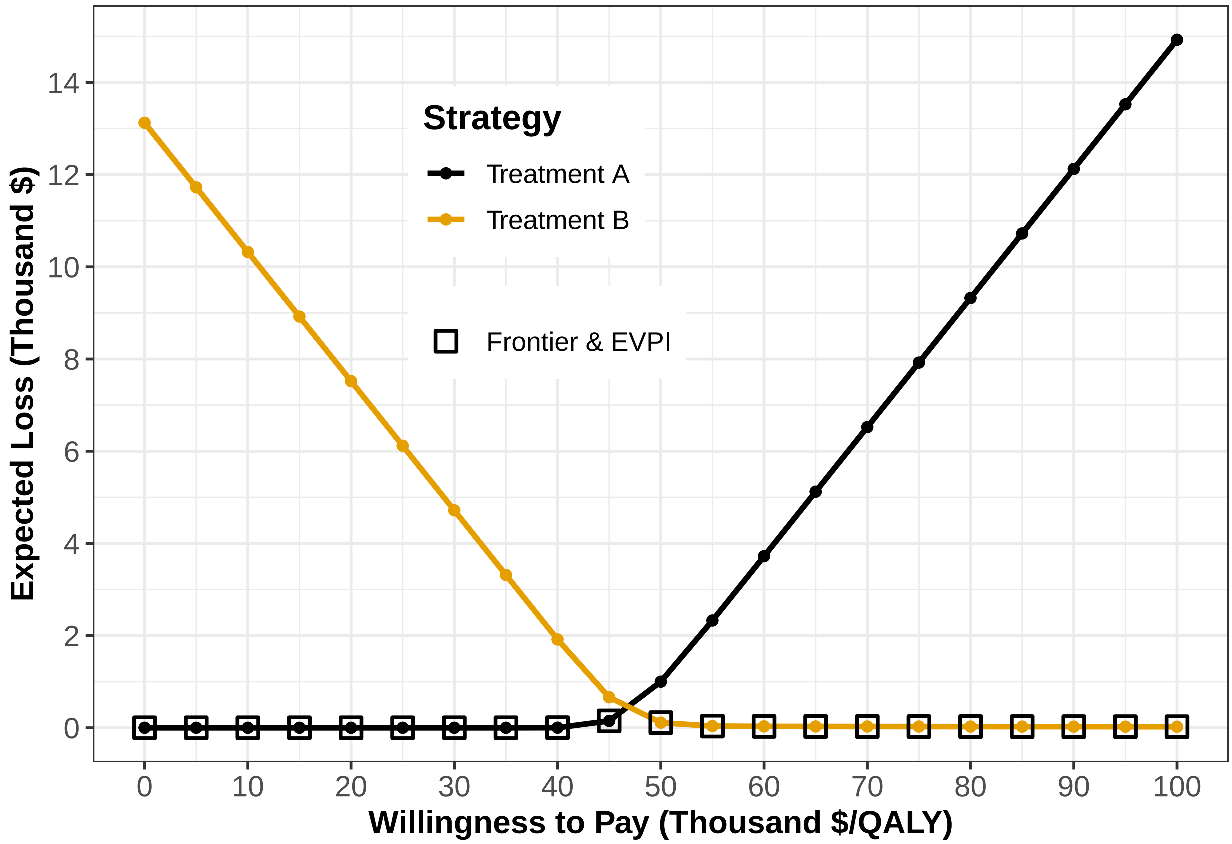
11.3.5 Expected Loss Curves (ELCs)

```
### Expected Loss Curves (ELCs)
elc_obj <- calc_exp_loss(wtp = v_wtp, psa = l_psa)
elc_obj
```

```
##        WTP    Strategy Expected_Loss On_Frontier
## 1        0 Treatment A      0.000000        TRUE
## 2        0 Treatment B  13126.032833       FALSE
## 3     5000 Treatment A      0.000000        TRUE
## 4     5000 Treatment B  11724.532073       FALSE
## 5    10000 Treatment A      0.000000        TRUE
## 6    10000 Treatment B  10323.031313       FALSE
## 7    15000 Treatment A      0.000000        TRUE
## 8    15000 Treatment B   8921.530552       FALSE
## 9    20000 Treatment A      0.000000        TRUE
## 10   20000 Treatment B   7520.029792       FALSE
## 11   25000 Treatment A      0.000000        TRUE
## 12   25000 Treatment B   6118.529032       FALSE
## 13   30000 Treatment A      0.000000        TRUE
## 14   30000 Treatment B   4717.028271       FALSE
## 15   35000 Treatment A      0.000000        TRUE
## 16   35000 Treatment B   3315.527511       FALSE
## 17   40000 Treatment A      1.834479        TRUE
## 18   40000 Treatment B   1915.861230       FALSE
## 19   45000 Treatment A    148.875620        TRUE
```

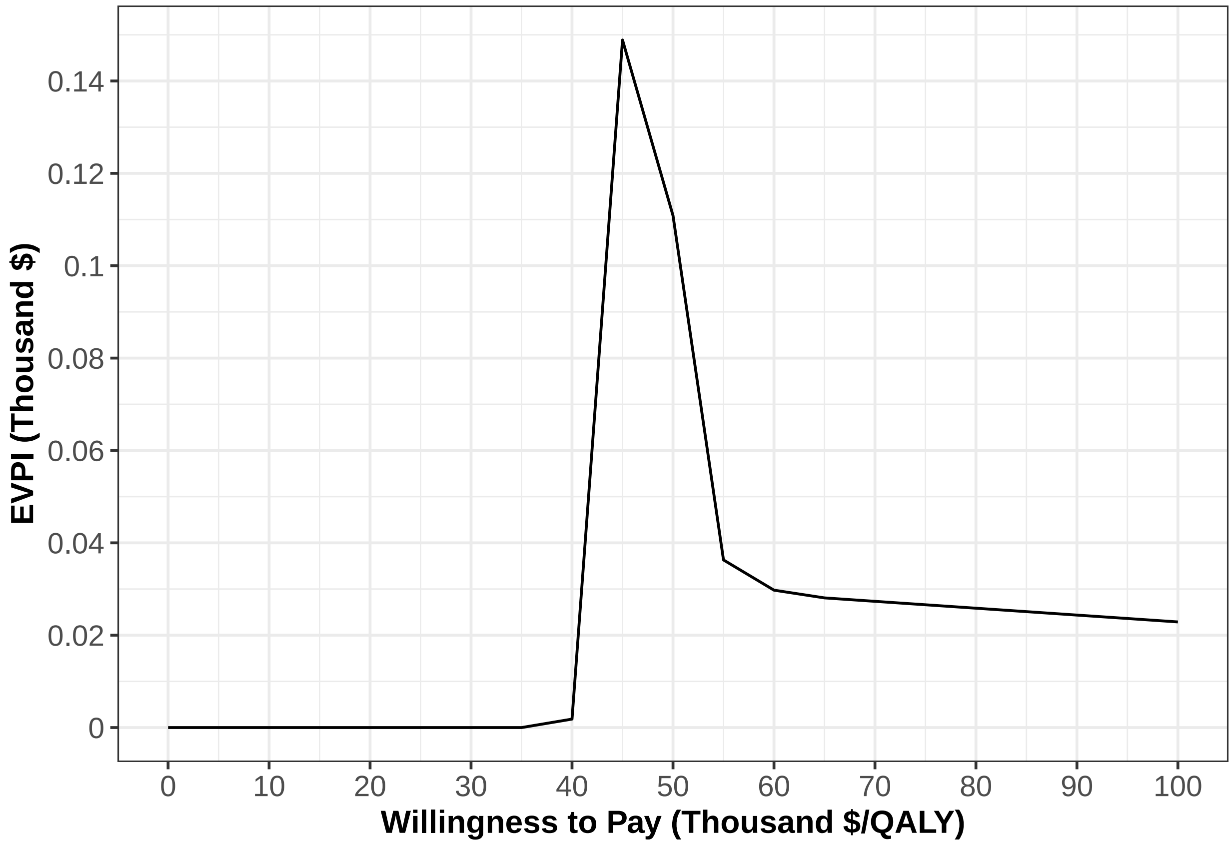
```
## 20  45000 Treatment B    661.401610       FALSE
## 21  50000 Treatment A    999.819901       FALSE
## 22  50000 Treatment B    110.845131        TRUE
## 23  55000 Treatment A   2326.770265       FALSE
## 24  55000 Treatment B     36.294734        TRUE
## 25  60000 Treatment A   3721.726427       FALSE
## 26  60000 Treatment B     29.750137        TRUE
## 27  65000 Treatment A   5121.551110       FALSE
## 28  65000 Treatment B     28.074059        TRUE
## 29  70000 Treatment A   6522.308375       FALSE
## 30  70000 Treatment B     27.330564        TRUE
## 31  75000 Treatment A   7923.065641       FALSE
## 32  75000 Treatment B     26.587069        TRUE
## 33  80000 Treatment A   9323.822907       FALSE
## 34  80000 Treatment B     25.843575        TRUE
## 35  85000 Treatment A  10724.580172       FALSE
## 36  85000 Treatment B     25.100080        TRUE
## 37  90000 Treatment A  12125.337438       FALSE
## 38  90000 Treatment B     24.356585        TRUE
## 39  95000 Treatment A  13526.094704       FALSE
## 40  95000 Treatment B     23.613091        TRUE
## 41 100000 Treatment A  14926.851969       FALSE
## 42 100000 Treatment B     22.869596        TRUE
```

```
# ELC plot
gg_elc <- plot_exp_loss(elc_obj, log_y = FALSE,
                txtsize = txtsize, xlim = c(0, NA), n_x_ticks = 14,
                col = "full") +
  ggthemes::scale_color_colorblind() +
  ggthemes::scale_fill_colorblind() +
  # geom_point(aes(shape = as.name("Strategy"))) +
  scale_y_continuous("Expected Loss (Thousand $)",
                     breaks = number_ticks(10),
                     labels = function(x) x/1000) +
  theme(legend.position = c(0.4, 0.7),)
gg_elc
```



11.3.6 Expected value of perfect information (EVPI)

```
### Expected value of perfect information (EVPI)
evpi <- calc_evpi(wtp = v_wtp, psa = l_psa)
# EVPI plot
gg_evpi <- plot_evpi(evpi, effect_units = "QALY",
                     txtsize = txtsize, xlim = c(0, NA), n_x_ticks = 14) +
  scale_y_continuous("EVPI (Thousand $)",
                     breaks = number_ticks(10),
                     labels = function(x) x/1000)
gg_evpi
```



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