

```
library(flexsurv)
library(boot)
library(randomForestSRC)
library(timeROC)
library(risksetROC)
source("stdca.R")
```

1 Preparation

Construct a *preoperative* function based on the Brennan nomogram. The preoperative nature will mean that most prognostic components will need to be marginalized out.

Variable	Preoperative?	Available?	Marginals
Age	Yes	Yes	Linear. 90 =>0, 30 =>8. Therefore $f(x) = -2/15(x - 90) = -2/15x + 12$
Sex	Yes	Yes	Male risk delta 3
Portal Vein	NO		14.4% YES, risk delta 10, marginal 1.4
Splenectomy	NO		9.9% YES, risk delta 62, marginal 6.1
Margin of resection	NO		20.7% POS, risk delta 4, marginal 0.8
Head.vs.Other	Yes	Yes	Head risk delta 51
Differentiation	NO		14.2% Well, risk delta 0, marginal 0 56.4% Mod, risk delta 14, marginal 7.9 29.5% Poor, risk delta 35, marginal 10.3. Overall marginal 18.2
Posterior.margin	NO		86.0% POS, risk delta 22, marginal 18.9
Numb.pos.nodes	NO		Mean 2.1, approx marginal 15
Numb.neg.nodes	NO		Mean 16.9, approx marginal 9
Back.pain	Yes	NO	13.7% YES, risk delta 15, marginal 2.0
T.stage	Yes	Yes	
Weight Loss	Yes	NO	53.7% YES, risk delta 3, marginal 1.6
Max.path.axis	Yes	Yes	

So the preoperative MSKCC score would be:

$$S = 1.4 + 6.1 + 0.8 + 18.2 + 18.9 + 15 + 9 + 15 * Back.pain + 3 * Weight.Loss + -2/15 * Age + 12 + 3 [Sex = M] + 51 [Head.vs.Other = Head] \quad (1)$$

```
fit.mskcc = list(
  inputs = list(
    History.Diagnosis.AgeAt = list(
      margins = data.frame(value = 65, fraction = 1),
      scorefunc = function(x) { x = x; -2/15*pmin(pmax(x, 0), 90) + 12 } ),
    Patient.Sex = list(
      margins = data.frame(value = c("M", "F"), fraction = c(0.501, 1-0.501)),
      scorefunc = function(x) { 3*I(x == "M") } ),
    Portal.Vein = list(
      margins = data.frame(value = c(TRUE, FALSE), fraction = c(0.144, 1-0.144)),
      scorefunc = function(x) { 10*I(x == TRUE) } ),
    Splenectomy = list(
      margins = data.frame(value = c(TRUE, FALSE), fraction = c(0.099, 1-0.099)),
      scorefunc = function(x) { 62*I(x == TRUE) } ),
    Treat.MarginPositive = list(
      margins = data.frame(value = c(TRUE, FALSE), fraction = c(0.207, 1-0.207)),
      scorefunc = function(x) { 4*I(x == TRUE) } ),
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Path.LocationBody = list(
  margins = data.frame(value = c(FALSE, TRUE), fraction = c(0.894, 1-0.894)),
  scorefunc = function(x) { 51*I(x == TRUE) }),
Path.Differentiation = list(
  margins = data.frame(value = c("1", "2", "3", "4"), fraction = c(0.142, 0.564, 1-0.142-0.564)),
  scorefunc = function(x) { 14*I(x == "2") + 35*I(x == "3") + 35*I(x == "4") }),
Posterior.Margin = list(
  margins = data.frame(value = c(TRUE, FALSE), fraction = c(0.86, 1-0.86)),
  scorefunc = function(x) { 22*I(x == TRUE) }),
Path.LN.Involved = list(
  margins = data.frame(value = 2.1, fraction = 1),
  scorefunc = function(x) {
    x = pmin(40, pmax(x, 0))
    fitfun = splinefun(c(0, 1, 2, 3, 4, 10, 15, 20, 25, 30, 35, 40), c(0, 14.56, 24.56, 30.56, 35.56, 40.56, 45.56, 50.56, 55.56, 60.56, 65.56, 70.56)),
    fitfun(x)
  }),
Path.LN.Negative = list(
  margins = data.frame(value = 16.9, fraction = 1),
  scorefunc = function(x) { (pmin(pmax(x, 0), 90)-90)*-11/90 }),
Back.pain = list(
  margins = data.frame(value = c(TRUE, FALSE), fraction = c(0.137, 1-0.137)),
  scorefunc = function(x) { 15*I(x == TRUE) }),
Stage.pT.Simplified = list(
  margins = data.frame(value = c("T1", "T2", "T34"), fraction = c(0.037, 0.119, 1-0.037-0.119)),
  scorefunc = function(x) { 36*I(x == "T1") + 11*I(x == "T34") }),
  # The following matches the original Brennan nomogram, but was not used as there are too
  # tumours in either the NSWPCN *or* the MSKCC cohorts -- how the T4 coefficient was even
  # I'll never know. The T34 coefficient of 11 was arrived at as (0.828*10+(1-0.037-0.119)*63)
  # being a frequency-weighted average of the T3 and T4 coefficients.
  # margins = data.frame(value = c("T1", "T2", "T3", "T4"), fraction = c(0.037, 0.119, 0.119, 0.725)),
  # scorefunc = function(x) { 36*I(x == "T1") + 10*I(x == "T3") + 63*I(x == "T4") }),
Weight.loss = list(
  margins = data.frame(value = c(TRUE, FALSE), fraction = c(0.537, 1-0.537)),
  scorefunc = function(x) { 3*I(x == TRUE) }),
Path.Size = list(
  margins = data.frame(),
  scorefunc = function(x) {
    x = pmin(16, pmax(x, 0))
    fitfun = splinefun(c(0, 1, 2, 3, 4, 6, 8, 10, 12, 14, 16), c(0, 29.74, 59.48, 89.22, 118.96, 148.70, 178.44, 208.18, 237.92, 267.66, 297.40)),
    fitfun(x)
  }) ),
outputs = list(
  DSS12mo = function(s) {
    x = pmax(50, pmin(350, s))
    fitfun = splinefun(c(79.0323, 115.02, 165.524, 197.278, 221.774, 242.339, 261.08), c(0, 10, 20, 30, 40, 50, 60)),
    y = fitfun(x)
    pmax(0, pmin(1, y))
  },
  DSS24mo = function(s) {
    x = pmax(50, pmin(350, s))
    fitfun = splinefun(c(71.1694, 97.7823, 129.536, 153.73, 174.294, 193.347, 211.79), c(0, 10, 20, 30, 40, 50, 60)),
    y = fitfun(x)
    pmax(0, pmin(1, y))
  }
)

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    },
    DSS36mo = function(s) {
      x = pmax(50, pmin(350, s))
      fitfun = splinefun(c(69.3548, 101.109, 125.302, 145.867, 164.919, 183.367, 202.7
      y = fitfun(x)
      pmax(0, pmin(1, y))
    })
  )

applyNomogram = function(nomogram, data)
{
  scores = rowSums(sapply(names(nomogram$inputs), function(input) {
    if (input %in% colnames(data)) {
      return(nomogram$inputs[[input]]$scorefunc(data[,input]))
    }
    warning(sprintf("Marginalizing missing variable: %s", input))
    margin_score = sum(nomogram$inputs[[input]]$scorefunc(nomogram$inputs[[input]]$margins$
    return(rep(margin_score, nrow(data)))
  })))

  outputs = sapply(nomogram$outputs, function(f) f(scores))
  cbind(Score = scores, outputs)
}

```

2 Model and data loading

Trained models:

```

temp = readRDS("05_final_model.rds")
fit.gg = temp$gg
fit.gg2 = temp$gg2
fit.cph = temp$cph
fit.km0 = temp$km0
fit.rsfc = temp$rsfc
data.nswpcn = temp$data.train

```

```

data.glasgow = readRDS("06_Glasgow.rds")
data.glasgow$Path.LN.Negative = data.glasgow$Path.LN.Inspected - data.glasgow$Path.LN.Involved
data.glasgow$History.Diagnosis.AgeAt = data.glasgow$History.Diagnosis.AgeAt.Cent + 68
data.glasgow$Path.Size = data.glasgow$Path.Size.Cent + 30
data.glasgow$SexM = data.glasgow$Patient.Sex == "M"
data.glasgow$AgeCent = data.glasgow$History.Diagnosis.AgeAt.Cent
data.glasgow$SizeCent = data.glasgow$Path.Size.Cent
data.glasgow$A2 = data.glasgow$Molec.S100A2.DCThresh
data.glasgow$A4 = data.glasgow$Molec.S100A4.DCThresh
data.glasgow$LocBody = data.glasgow$Path.Location != "HOP"
data.glasgow$Time = data.glasgow$History.Death.EventTimeDays
data.glasgow$DSD = data.glasgow$History.DSDeath.Event

```

3 Score calculation

```

temp = applyNomogram(fit.mskcc, data.glasgow)

## Warning in FUN(c("History.Diagnosis.AgeAt", "Patient.Sex", "Portal.Vein", : Marginalizing
missing variable: Portal.Vein
## Warning in FUN(c("History.Diagnosis.AgeAt", "Patient.Sex", "Portal.Vein", : Marginalizing
missing variable: Splenectomy
## Warning in FUN(c("History.Diagnosis.AgeAt", "Patient.Sex", "Portal.Vein", : Marginalizing
missing variable: Posterior.Margin
## Warning in FUN(c("History.Diagnosis.AgeAt", "Patient.Sex", "Portal.Vein", : Marginalizing
missing variable: Back.pain
## Warning in FUN(c("History.Diagnosis.AgeAt", "Patient.Sex", "Portal.Vein", : Marginalizing
missing variable: Weight.loss

mskcc_post.linpred.glasgow = temp[,1]
mskcc_post.12mo.glasgow = temp[,2]
mskcc_post.24mo.glasgow = temp[,3]
mskcc_post.36mo.glasgow = temp[,4]
temp = applyNomogram(fit.mskcc, data.glasgow[,c("History.Diagnosis.AgeAt", "Patient.Sex", "Path.Location", "Path.Differentiation", "Treat.MarginPositive", "Posterior.Margin", "Path.LN.Involved", "Path.LN.Negative", "Back.pain", "Weight.loss")])

## Warning in FUN(c("History.Diagnosis.AgeAt", "Patient.Sex", "Portal.Vein", : Marginalizing
missing variable: Portal.Vein
## Warning in FUN(c("History.Diagnosis.AgeAt", "Patient.Sex", "Portal.Vein", : Marginalizing
missing variable: Splenectomy
## Warning in FUN(c("History.Diagnosis.AgeAt", "Patient.Sex", "Portal.Vein", : Marginalizing
missing variable: Treat.MarginPositive
## Warning in FUN(c("History.Diagnosis.AgeAt", "Patient.Sex", "Portal.Vein", : Marginalizing
missing variable: Path.Differentiation
## Warning in FUN(c("History.Diagnosis.AgeAt", "Patient.Sex", "Portal.Vein", : Marginalizing
missing variable: Posterior.Margin
## Warning in FUN(c("History.Diagnosis.AgeAt", "Patient.Sex", "Portal.Vein", : Marginalizing
missing variable: Path.LN.Involved
## Warning in FUN(c("History.Diagnosis.AgeAt", "Patient.Sex", "Portal.Vein", : Marginalizing
missing variable: Path.LN.Negative
## Warning in FUN(c("History.Diagnosis.AgeAt", "Patient.Sex", "Portal.Vein", : Marginalizing
missing variable: Back.pain
## Warning in FUN(c("History.Diagnosis.AgeAt", "Patient.Sex", "Portal.Vein", : Marginalizing
missing variable: Weight.loss

mskcc_pre.linpred.glasgow = temp[,1]
mskcc_pre.12mo.glasgow = temp[,2]
mskcc_pre.24mo.glasgow = temp[,3]
mskcc_pre.36mo.glasgow = temp[,4]

```

Get approximate linear predictors from the GG model, by just calculating the location term effect.

```

val.prob.times = seq(0, max(data.glasgow$Time), 1)

gg.path.glasgow = summary(fit.gg, newdata = data.glasgow, ci = FALSE)
temp.coefs = coef(fit.gg)
gg.linpred.glasgow = sapply(1:length(temp.coefs), function(coef_i) {
  if (names(temp.coefs)[coef_i] %in% colnames(data.glasgow)) {
    temp.coefs[coef_i] * data.glasgow[,names(temp.coefs)[coef_i]]
  } else if (gsub("TRUE$", "", names(temp.coefs)[coef_i]) %in% colnames(data.glasgow)) {
    temp.coefs[coef_i] * data.glasgow[,gsub("TRUE$", "", names(temp.coefs)[coef_i])]
  } else {

```

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        rep(0, nrow(data.glasgow))
    } })
gg.linpred.glasgow = -rowSums(gg.linpred.glasgow) # Negate to bring into concordance with the direction
temp = summary(fit.gg, newdata = data.glasgow, ci = FALSE)
gg.prob.glasgow = sapply(temp, function(x) approx(x[,1], x[,2], xout = val.prob.times, yleft = 1, yright = 0))
colnames(gg.prob.glasgow) = rownames(data.glasgow)

gg.linpred.nswpcn = sapply(1:length(temp.coefs), function(coef_i) {
  if (names(temp.coefs)[coef_i] %in% colnames(data.nswpcn)) {
    temp.coefs[coef_i] * data.nswpcn[,names(temp.coefs)[coef_i]]
  } else if (gsub("TRUE$", "", names(temp.coefs)[coef_i]) %in% colnames(data.nswpcn)) {
    temp.coefs[coef_i] * data.nswpcn[,gsub("TRUE$", "", names(temp.coefs)[coef_i])]
  } else {
    rep(0, nrow(data.nswpcn))
  } })
gg.linpred.nswpcn = -rowSums(gg.linpred.nswpcn) # Negate to bring into concordance with the direction
temp = summary(fit.gg, newdata = data.nswpcn, ci = FALSE)
gg.prob.nswpcn = sapply(temp, function(x) approx(x[,1], x[,2], xout = val.prob.times, yleft = 1, yright = 0))
colnames(gg.prob.nswpcn) = rownames(data.nswpcn)

```

And the GG2

```

gg2.path.glasgow = summary(fit.gg2, newdata = data.glasgow, ci = FALSE)
temp.coefs = coef(fit.gg2)
gg2.linpred.glasgow = sapply(1:length(temp.coefs), function(coef_i) {
  if (names(temp.coefs)[coef_i] %in% colnames(data.glasgow)) {
    temp.coefs[coef_i] * data.glasgow[,names(temp.coefs)[coef_i]]
  } else if (gsub("TRUE$", "", names(temp.coefs)[coef_i]) %in% colnames(data.glasgow)) {
    temp.coefs[coef_i] * data.glasgow[,gsub("TRUE$", "", names(temp.coefs)[coef_i])]
  } else {
    rep(0, nrow(data.glasgow))
  } })
gg2.linpred.glasgow = -rowSums(gg2.linpred.glasgow) # Negate to bring into concordance with the direction
temp = summary(fit.gg2, newdata = data.glasgow, ci = FALSE)
gg2.prob.glasgow = sapply(temp, function(x) approx(x[,1], x[,2], xout = val.prob.times, yleft = 1, yright = 0))
colnames(gg2.prob.glasgow) = rownames(data.glasgow)

gg2.linpred.nswpcn = sapply(1:length(temp.coefs), function(coef_i) {
  if (names(temp.coefs)[coef_i] %in% colnames(data.nswpcn)) {
    temp.coefs[coef_i] * data.nswpcn[,names(temp.coefs)[coef_i]]
  } else if (gsub("TRUE$", "", names(temp.coefs)[coef_i]) %in% colnames(data.nswpcn)) {
    temp.coefs[coef_i] * data.nswpcn[,gsub("TRUE$", "", names(temp.coefs)[coef_i])]
  } else {
    rep(0, nrow(data.nswpcn))
  } })
gg2.linpred.nswpcn = -rowSums(gg2.linpred.nswpcn) # Negate to bring into concordance with the direction
temp = summary(fit.gg2, newdata = data.nswpcn, ci = FALSE)
gg2.prob.nswpcn = sapply(temp, function(x) approx(x[,1], x[,2], xout = val.prob.times, yleft = 1, yright = 0))
colnames(gg2.prob.nswpcn) = rownames(data.nswpcn)

```

```

temp.coefs = coef(fit.cph)
cph.linpred.glasgow = sapply(1:length(temp.coefs), function(coef_i) {
  if (names(temp.coefs)[coef_i] %in% colnames(data.glasgow)) {

```

```

        temp.coefs[coef_i] * data.glasgow[,names(temp.coefs)[coef_i]]
    } else if (gsub("TRUE$", "", names(temp.coefs)[coef_i]) %in% colnames(data.glasgow)) {
        temp.coefs[coef_i] * data.glasgow[,gsub("TRUE$", "", names(temp.coefs)[coef_i])]
    } else {
        rep(0, nrow(data.glasgow))
    } })
cph.linpred.glasgow = rowSums(cph.linpred.glasgow)
temp = survfit(fit.cph, newdata = data.glasgow)
cph.prob.glasgow = simplify2array(tapply(1:length(temp$surv), rep(names(temp$strata), temp$strata), function(x) {
    temp.coefs[coef_i] * data.glasgow[,names(temp.coefs)[coef_i]]
} else if (gsub("TRUE$", "", names(temp.coefs)[coef_i]) %in% colnames(data.glasgow)) {
    temp.coefs[coef_i] * data.glasgow[,gsub("TRUE$", "", names(temp.coefs)[coef_i])]
} else {
    rep(0, nrow(data.glasgow))
} })))

cph.linpred.nswpcn = sapply(1:length(temp.coefs), function(coef_i) {
    if (names(temp.coefs)[coef_i] %in% colnames(data.nswpcn)) {
        temp.coefs[coef_i] * data.nswpcn[,names(temp.coefs)[coef_i]]
    } else if (gsub("TRUE$", "", names(temp.coefs)[coef_i]) %in% colnames(data.nswpcn)) {
        temp.coefs[coef_i] * data.nswpcn[,gsub("TRUE$", "", names(temp.coefs)[coef_i])]
    } else {
        rep(0, nrow(data.nswpcn))
    } })
cph.linpred.nswpcn = rowSums(cph.linpred.nswpcn)
temp = survfit(fit.cph, newdata = data.nswpcn)
cph.prob.nswpcn = simplify2array(tapply(1:length(temp$surv), rep(names(temp$strata), temp$strata), function(x) {
    temp.coefs[coef_i] * data.nswpcn[,names(temp.coefs)[coef_i]]
} else if (gsub("TRUE$", "", names(temp.coefs)[coef_i]) %in% colnames(data.nswpcn)) {
    temp.coefs[coef_i] * data.nswpcn[,gsub("TRUE$", "", names(temp.coefs)[coef_i])]
} else {
    rep(0, nrow(data.nswpcn))
} })))

# Doesn't work for some obscure reason, I suspect to do with strata and environments:
# cph.linpred.glasgow = predict(fit.cph, newdata = data.glasgow)
# cph.linpred.nswpcn = predict(fit.cph, newdata = data.nswpcn)

```

```

temp = predict(fit.rsrf, newdata = data.glasgow)
rsf.linpred.glasgow = apply(temp$survival, 1, function(s1) {
    sfunc = approxfun(temp$time.interest, s1, yleft = 1, yright = 0, rule = 2)
    med = uniroot(function(x) sfunc(x) - 0.5, lower = min(temp$time.interest), upper = max(temp$time.interest))
    med
})
rsf.linpred.glasgow = -rsf.linpred.glasgow
rsf.prob.glasgow = apply(temp$survival, 1, function(s1) approx(temp$time.interest, s1, xout = val.prob.t, rule = 2))
colnames(rsf.prob.glasgow) = rownames(data.glasgow)

temp = predict(fit.rsrf, newdata = data.nswpcn)
rsf.linpred.nswpcn = apply(temp$survival, 1, function(s1) {
    sfunc = approxfun(temp$time.interest, s1, yleft = 1, yright = 0, rule = 2)
    med = uniroot(function(x) sfunc(x) - 0.5, lower = min(temp$time.interest), upper = max(temp$time.interest))
    med
})
rsf.linpred.nswpcn = -rsf.linpred.nswpcn
rsf.prob.nswpcn = apply(temp$survival, 1, function(s1) approx(temp$time.interest, s1, xout = val.prob.t, rule = 2))
colnames(rsf.prob.nswpcn) = rownames(data.nswpcn)

```

4 Validation

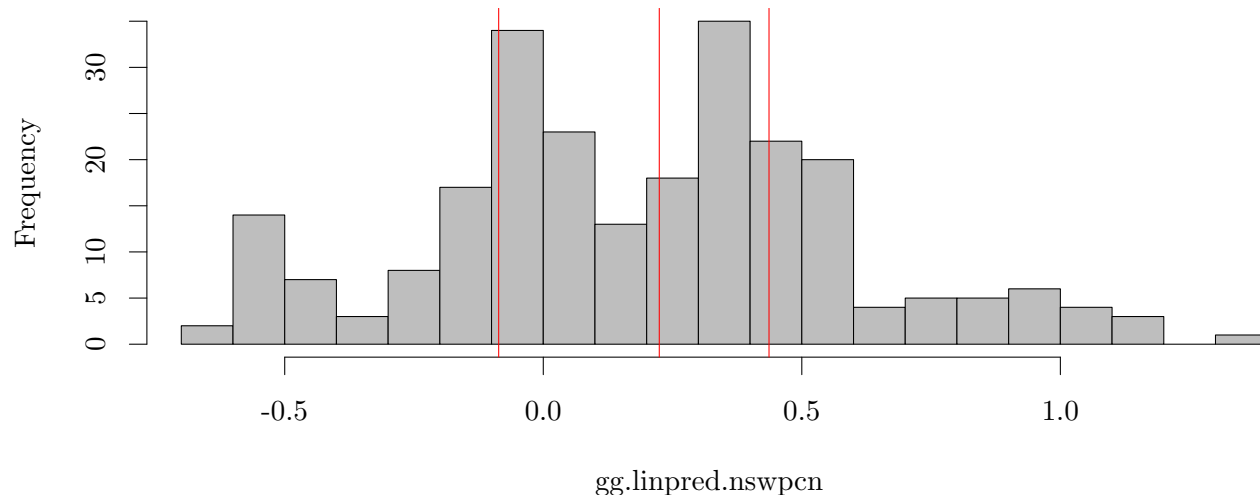
4.1 Altman diagnostic 1: score histograms

```

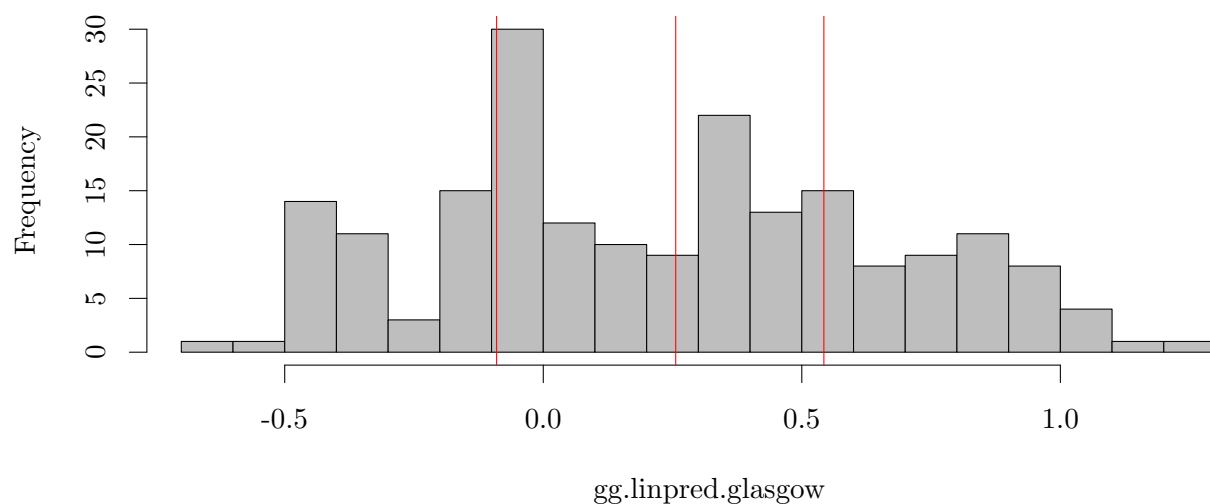
par(mfrow = c(2, 1))
hist(gg.linpred.nswpcn, main = "NSWPCN GG scores", xlim = range(c(gg.linpred.nswpcn, gg.linpred.glasgow)),
abline(v = quantile(gg.linpred.nswpcn, probs = c(0.25, 0.5, 0.75)), col = "red")
hist(gg.linpred.glasgow, main = "Glasgow GG scores", xlim = range(c(gg.linpred.nswpcn, gg.linpred.glasgow)),
abline(v = quantile(gg.linpred.glasgow, probs = c(0.25, 0.5, 0.75)), col = "red")

```

NSWPCN GG scores



Glasgow GG scores



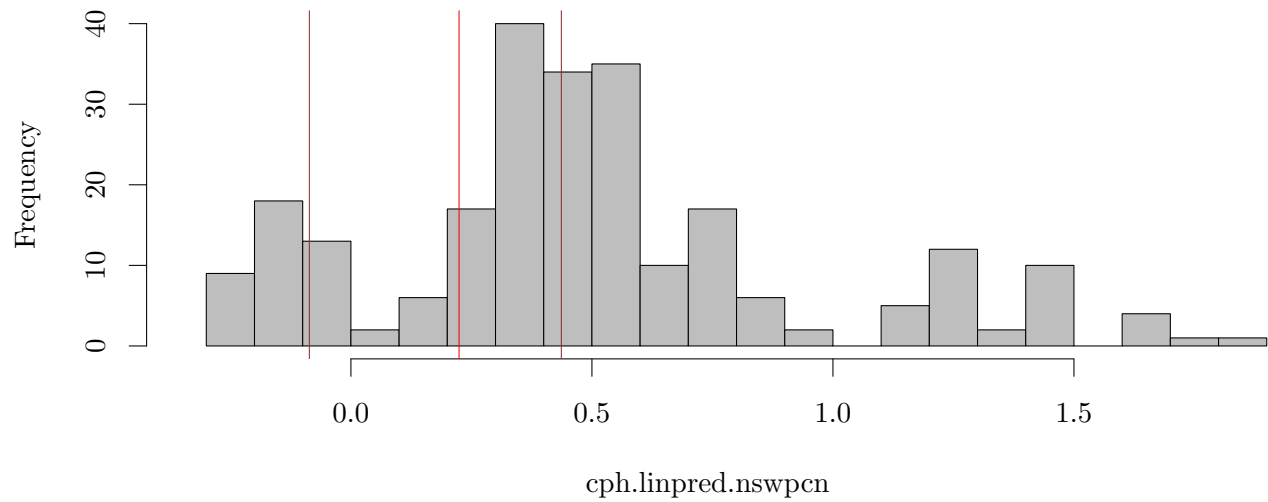
```

par(mfrow = c(1, 1))

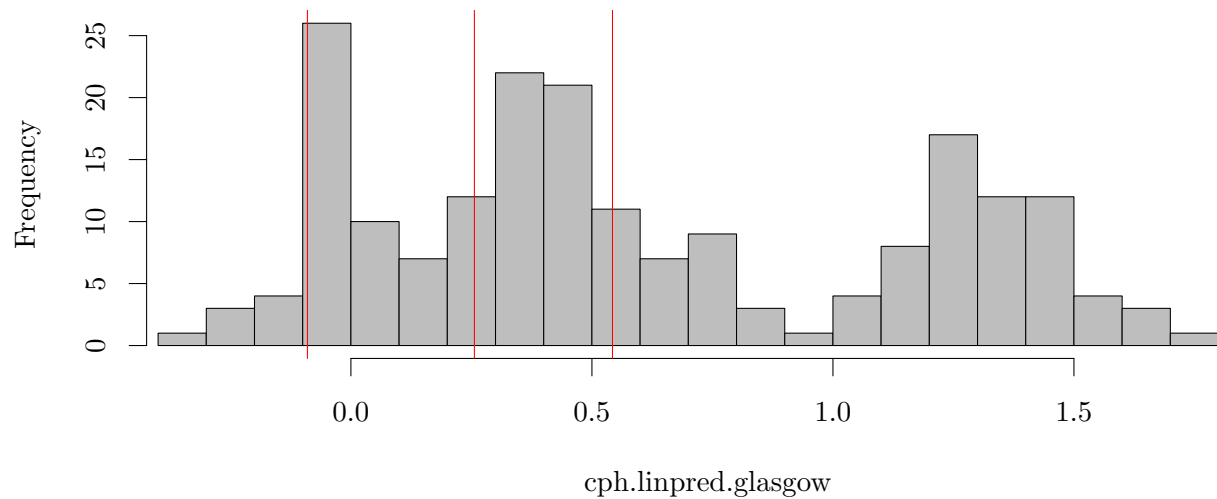
par(mfrow = c(2, 1))
hist(cph.linpred.nswpcn, main = "NSWPCN CPH scores", xlim = range(c(cph.linpred.nswpcn, cph.linpred.glasgow)),
abline(v = quantile(gg.linpred.nswpcn, probs = c(0.25, 0.5, 0.75)), col = "red")
hist(cph.linpred.glasgow, main = "Glasgow CPH scores", xlim = range(c(cph.linpred.nswpcn, cph.linpred.glasgow)),
abline(v = quantile(gg.linpred.glasgow, probs = c(0.25, 0.5, 0.75)), col = "red")

```

NSWPCN CPH scores

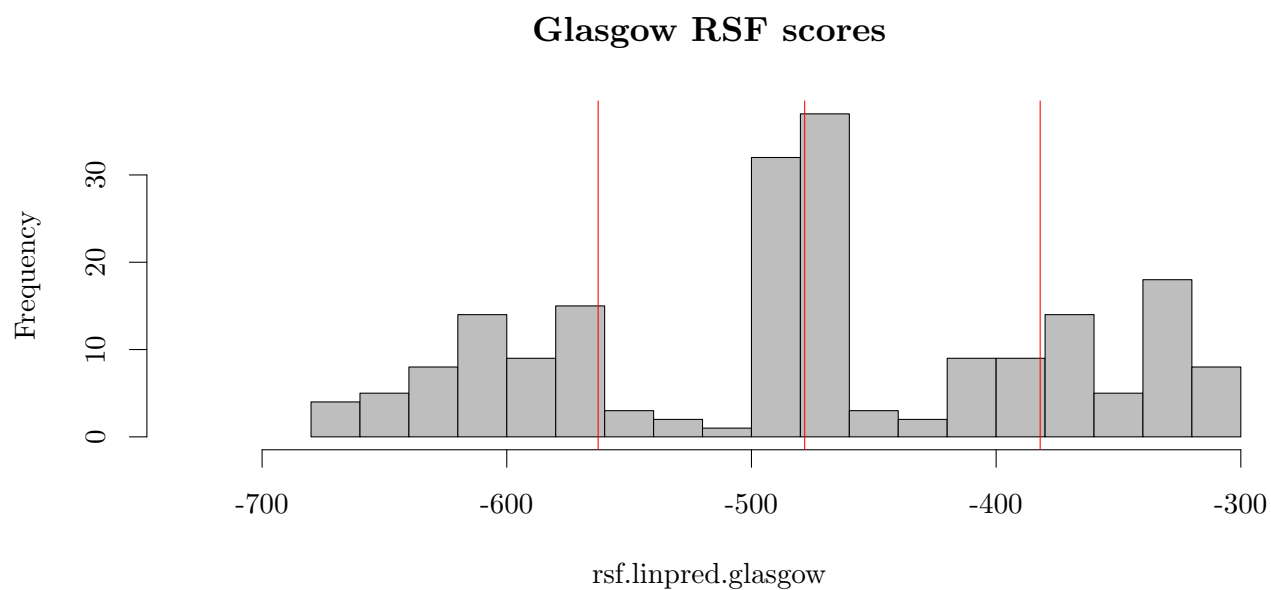
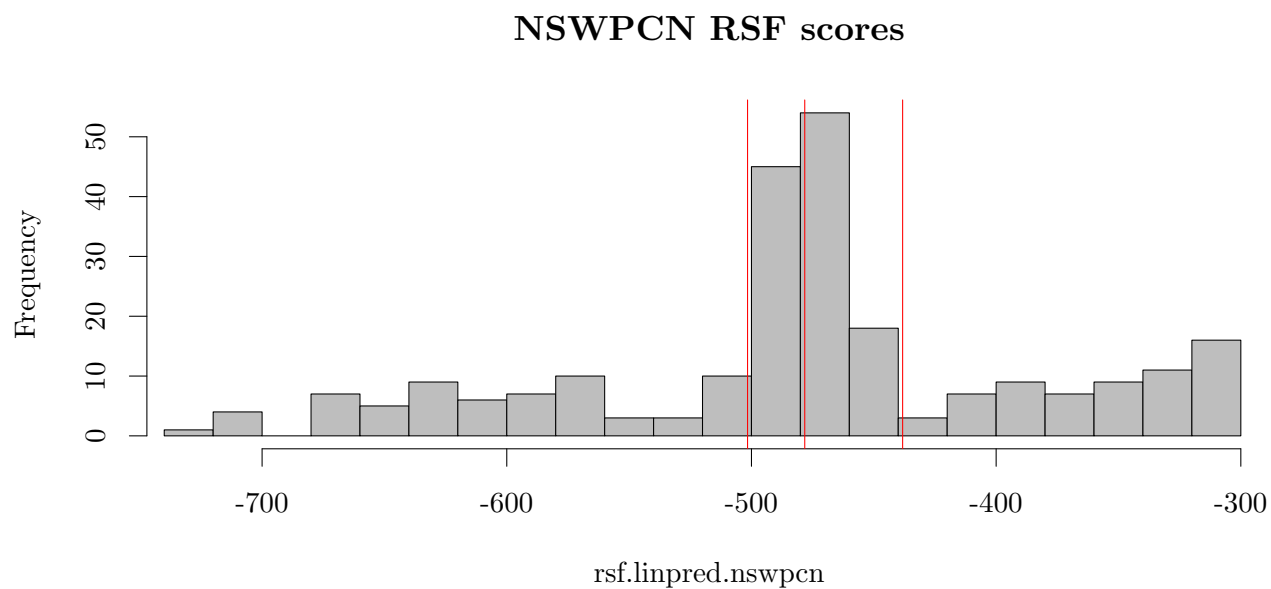


Glasgow CPH scores



```
par(mfrow = c(1, 1))

par(mfrow = c(2, 1))
hist(rsf.linpred.nswpcn, main = "NSWPCN RSF scores", xlim = range(c(rsf.linpred.nswpcn, rsf.linpred.glasgow)), col = "gray", border = "black")
abline(v = quantile(rsf.linpred.nswpcn, probs = c(0.25, 0.5, 0.75)), col = "red")
hist(rsf.linpred.glasgow, main = "Glasgow RSF scores", xlim = range(c(rsf.linpred.nswpcn, rsf.linpred.glasgow)), col = "gray", border = "black")
abline(v = quantile(rsf.linpred.glasgow, probs = c(0.25, 0.5, 0.75)), col = "red")
```

```
par(mfrow = c(1, 1))
```

4.2 Altman method 1 (D,F)

```
summary(coxph(Surv(Time, DSD) ~ mskcc_post.linpred.glasgow, data.glasgow))

## Call:
## coxph(formula = Surv(Time, DSD) ~ mskcc_post.linpred.glasgow,
##       data = data.glasgow)
##
##      n= 198, number of events= 170
##
```

```
##               coef exp(coef) se(coef)      z Pr(>|z|)
## mskcc_post.linpred.glasgow 0.01484  1.01495  0.00405 3.67  0.00025
##
##               exp(coef) exp(-coef) lower .95 upper .95
## mskcc_post.linpred.glasgow      1.01      0.985      1.01      1.02
##
## Concordance= 0.576 (se = 0.025 )
## Rsquare= 0.067 (max possible= 0.999 )
## Likelihood ratio test= 13.6 on 1 df,  p=0.000221
## Wald test = 13.4 on 1 df,  p=0.000245
## Score (logrank) test = 13.6 on 1 df,  p=0.000229

summary(coxph(Surv(Time, DSD) ~ mskcc_pre.linpred.glasgow, data.glasgow))

## Call:
## coxph(formula = Surv(Time, DSD) ~ mskcc_pre.linpred.glasgow,
##       data = data.glasgow)
##
## n= 198, number of events= 170
##
##               coef exp(coef) se(coef)      z Pr(>|z|)
## mskcc_pre.linpred.glasgow -0.000423  0.999577  0.007318 -0.06  0.95
##
##               exp(coef) exp(-coef) lower .95 upper .95
## mskcc_pre.linpred.glasgow      1      1      0.985      1.01
##
## Concordance= 0.421 (se = 0.025 )
## Rsquare= 0 (max possible= 0.999 )
## Likelihood ratio test= 0 on 1 df,  p=0.954
## Wald test = 0 on 1 df,  p=0.954
## Score (logrank) test = 0 on 1 df,  p=0.954

summary(coxph(Surv(Time, DSD) ~ gg.linpred.glasgow, data.glasgow))

## Call:
## coxph(formula = Surv(Time, DSD) ~ gg.linpred.glasgow, data = data.glasgow)
##
## n= 198, number of events= 170
##
##               coef exp(coef) se(coef)      z Pr(>|z|)
## gg.linpred.glasgow 0.730  2.076  0.192 3.8  0.00014
##
##               exp(coef) exp(-coef) lower .95 upper .95
## gg.linpred.glasgow  2.08  0.482  1.42  3.03
##
## Concordance= 0.611 (se = 0.025 )
## Rsquare= 0.07 (max possible= 0.999 )
## Likelihood ratio test= 14.4 on 1 df,  p=0.000149
## Wald test = 14.4 on 1 df,  p=0.000144
## Score (logrank) test = 14.6 on 1 df,  p=0.000131

summary(coxph(Surv(Time, DSD) ~ cph.linpred.glasgow, data.glasgow))

## Call:
## coxph(formula = Surv(Time, DSD) ~ cph.linpred.glasgow, data = data.glasgow)
```

```
##
##   n= 198, number of events= 170
##
##               coef exp(coef) se(coef)      z Pr(>|z|)
## cph.linpred.glasgow 0.853      2.347    0.150 5.68  1.4e-08
##
##               exp(coef) exp(-coef) lower .95 upper .95
## cph.linpred.glasgow      2.35      0.426      1.75      3.15
##
## Concordance= 0.657 (se = 0.025 )
## Rsquare= 0.145 (max possible= 0.999 )
## Likelihood ratio test= 31 on 1 df,  p=2.63e-08
## Wald test = 32.2 on 1 df,  p=1.37e-08
## Score (logrank) test = 33.5 on 1 df,  p=7.15e-09

summary(coxph(Surv(Time, DSD) ~ rsf.linpred.glasgow, data.glasgow))

## Call:
## coxph(formula = Surv(Time, DSD) ~ rsf.linpred.glasgow, data = data.glasgow)
##
##   n= 198, number of events= 170
##
##               coef exp(coef) se(coef)      z Pr(>|z|)
## rsf.linpred.glasgow 0.003223  1.003228 0.000807 3.99  6.5e-05
##
##               exp(coef) exp(-coef) lower .95 upper .95
## rsf.linpred.glasgow      1      0.997      1      1
##
## Concordance= 0.614 (se = 0.025 )
## Rsquare= 0.078 (max possible= 0.999 )
## Likelihood ratio test= 16 on 1 df,  p=6.36e-05
## Wald test = 15.9 on 1 df,  p=6.55e-05
## Score (logrank) test = 16.2 on 1 df,  p=5.8e-05

anova(coxph(Surv(Time, DSD) ~ offset(gg.linpred.glasgow) + gg.linpred.glasgow, data.glasgow))

## Analysis of Deviance Table
## Cox model: response is Surv(Time, DSD)
## Terms added sequentially (first to last)
##
##               loglik Chisq Df Pr(>|Chi|)
## NULL                -723
## gg.linpred.glasgow  -722  1.97  1      0.16

anova(coxph(Surv(Time, DSD) ~ offset(cph.linpred.glasgow) + cph.linpred.glasgow, data.glasgow))

## Analysis of Deviance Table
## Cox model: response is Surv(Time, DSD)
## Terms added sequentially (first to last)
##
##               loglik Chisq Df Pr(>|Chi|)
## NULL                -714
## cph.linpred.glasgow  -714  0.96  1      0.33

anova(coxph(Surv(Time, DSD) ~ offset(rsf.linpred.glasgow) + rsf.linpred.glasgow, data.glasgow))
```

```
## Warning in fitter(X, Y, strats, offset, init, control, weights = weights, : Ran out of
iterations and did not converge
## Error in fitter(X, Y, strats, offset, init, control, weights = weights, : NA/NaN/Inf in
foreign function call (arg 6)
```

Booyah.

4.3 Altman method 2 (F)

```
summary(coxph(Surv(Time, DSD) ~ offset(mskcc_pre.linpred.glasgow) + AgeCent + SexM + SizeCent + A2 + A4, data = data.glasgow))

## Warning in fitter(X, Y, strats, offset, init, control, weights = weights, : Ran out of
iterations and did not converge
## Error in fitter(X, Y, strats, offset, init, control, weights = weights, : NA/NaN/Inf in
foreign function call (arg 6)

summary(coxph(Surv(Time, DSD) ~ offset(mskcc_post.linpred.glasgow) + AgeCent + SexM + SizeCent + A2 + A4, data = data.glasgow))

## Call:
## coxph(formula = Surv(Time, DSD) ~ offset(mskcc_post.linpred.glasgow) +
##      AgeCent + SexM + SizeCent + A2 + A4, data = data.glasgow)
##
##      n= 198, number of events= 170
##
##              coef exp(coef)  se(coef)      z Pr(>|z|)
## AgeCent      0.22831   1.25648   0.01006   22.69 < 2e-16
## SexMTRUE     -5.22725   0.00537   0.30189  -17.32 < 2e-16
## SizeCent      0.14973   1.16152   0.01910    7.84 4.6e-15
## A2TRUE        -2.29883   0.10038   0.37880   -6.07 1.3e-09
## A4TRUE         4.93307  138.80556   0.29941   16.48 < 2e-16
##
##      exp(coef) exp(-coef) lower .95 upper .95
## AgeCent    1.26e+00    0.7959   1.23194   1.2815
## SexMTRUE    5.37e-03   186.2805   0.00297   0.0097
## SizeCent    1.16e+00    0.8609   1.11884   1.2058
## A2TRUE      1.00e-01    9.9625   0.04777   0.2109
## A4TRUE      1.39e+02    0.0072  77.18720  249.6137
##
## Concordance= 0.587 (se = 0.025 )
## Rsquare= 1 (max possible= 1 )
## Likelihood ratio test= 1719 on 5 df, p=0
## Wald test              = 2210 on 5 df, p=0
## Score (logrank) test = 12193 on 5 df, p=0

summary(coxph(Surv(Time, DSD) ~ offset(gg.linpred.glasgow) + AgeCent + SexM + SizeCent + A2 + A4, data = data.glasgow))

## Call:
## coxph(formula = Surv(Time, DSD) ~ offset(gg.linpred.glasgow) +
##      AgeCent + SexM + SizeCent + A2 + A4, data = data.glasgow)
##
##      n= 198, number of events= 170
##
##              coef exp(coef) se(coef)      z Pr(>|z|)
## AgeCent     -0.03255   0.96797  0.00860   -3.78 0.00015
```

```

## SexMTRUE 0.68806 1.98986 0.16160 4.26 2.1e-05
## SizeCent 0.02286 1.02312 0.00737 3.10 0.00194
## A2TRUE 0.21044 1.23422 0.17387 1.21 0.22615
## A4TRUE -0.06252 0.93940 0.17723 -0.35 0.72427
##
## exp(coef) exp(-coef) lower .95 upper .95
## AgeCent 0.968 1.033 0.952 0.984
## SexMTRUE 1.990 0.503 1.450 2.731
## SizeCent 1.023 0.977 1.008 1.038
## A2TRUE 1.234 0.810 0.878 1.735
## A4TRUE 0.939 1.065 0.664 1.330
##
## Concordance= 0.681 (se = 0.025 )
## Rsquare= 0.196 (max possible= 0.999 )
## Likelihood ratio test= 43.3 on 5 df, p=3.23e-08
## Wald test = 44.2 on 5 df, p=2.13e-08
## Score (logrank) test = 46.1 on 5 df, p=8.77e-09

summary(coxph(Surv(Time, DSD) ~ offset(cph.linpred.glasgow) + AgeCent + SexM + SizeCent + A2 + A4, data.

## Call:
## coxph(formula = Surv(Time, DSD) ~ offset(cph.linpred.glasgow) +
## AgeCent + SexM + SizeCent + A2 + A4, data = data.glasgow)
##
## n= 198, number of events= 170
##
## coef exp(coef) se(coef) z Pr(>|z|)
## AgeCent -0.03255 0.96797 0.00860 -3.78 0.00015
## SexMTRUE 0.26736 1.30651 0.16160 1.65 0.09803
## SizeCent 0.01997 1.02017 0.00737 2.71 0.00677
## A2TRUE -0.10278 0.90232 0.17387 -0.59 0.55443
## A4TRUE -0.12400 0.88338 0.17723 -0.70 0.48414
##
## exp(coef) exp(-coef) lower .95 upper .95
## AgeCent 0.968 1.033 0.952 0.984
## SexMTRUE 1.307 0.765 0.952 1.793
## SizeCent 1.020 0.980 1.006 1.035
## A2TRUE 0.902 1.108 0.642 1.269
## A4TRUE 0.883 1.132 0.624 1.250
##
## Concordance= 0.681 (se = 0.025 )
## Rsquare= 0.122 (max possible= 0.999 )
## Likelihood ratio test= 25.7 on 5 df, p=0.000102
## Wald test = 26.9 on 5 df, p=5.89e-05
## Score (logrank) test = 27.4 on 5 df, p=4.78e-05

summary(coxph(Surv(Time, DSD) ~ offset(rsf.linpred.glasgow) + AgeCent + SexM + SizeCent + A2 + A4, data.

## Warning in fitter(X, Y, strats, offset, init, control, weights = weights, : Ran out of
iterations and did not converge
## Error in fitter(X, Y, strats, offset, init, control, weights = weights, : NA/NaN/Inf in
foreign function call (arg 6)

```

Still strong evidence of misspecification or poor fit. However, the above calibration slope was not significantly different from 1. Hmm. This doesn't necessarily sink the method, but will need checking as we go

along.

4.4 Altman method 3 (D)

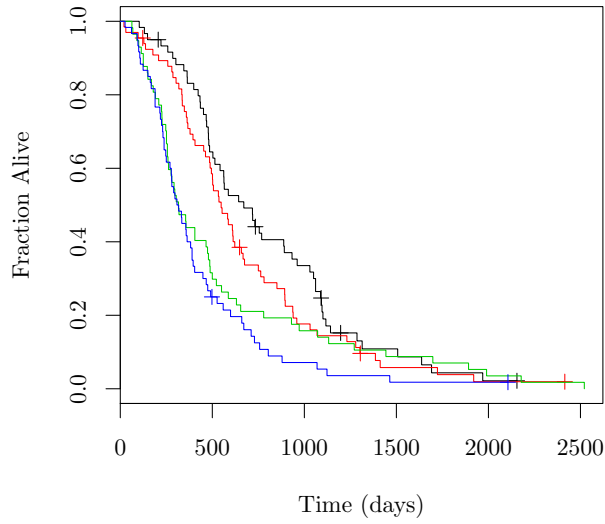
Look at the CIs above.

4.5 Altman method 4 (D,C)

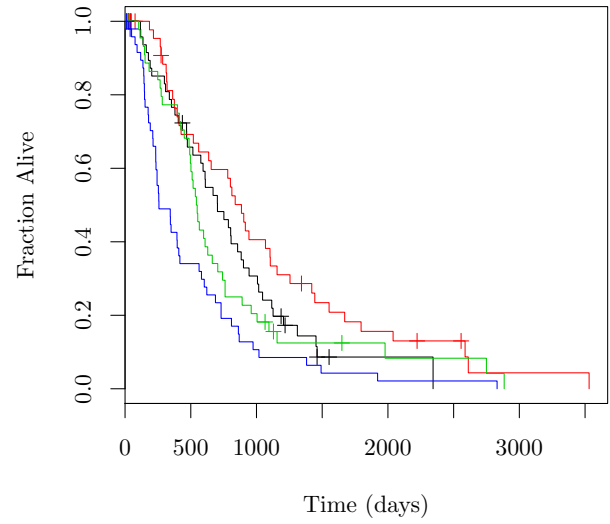
```
group_quantiles = c(0, 0.25, 0.5, 0.75, 1)
mskcc_pre.groups.glasgow = cut(mskcc_pre.linpred.glasgow, quantile(mskcc_pre.linpred.glasgow, group_quantiles))
mskcc_post.groups.glasgow = cut(mskcc_post.linpred.glasgow, quantile(mskcc_post.linpred.glasgow, group_quantiles))
gg.groups.glasgow = cut(gg.linpred.glasgow, quantile(gg.linpred.glasgow, group_quantiles))
gg.groups.nswpcn = cut(gg.linpred.nswpcn, quantile(gg.linpred.nswpcn, group_quantiles))
cph.groups.glasgow = cut(cph.linpred.glasgow, quantile(cph.linpred.glasgow, group_quantiles))
cph.groups.nswpcn = cut(cph.linpred.nswpcn, quantile(cph.linpred.nswpcn, group_quantiles))
rsf.groups.glasgow = cut(rsf.linpred.glasgow, quantile(rsf.linpred.glasgow, group_quantiles))
rsf.groups.nswpcn = cut(rsf.linpred.nswpcn, quantile(rsf.linpred.nswpcn, group_quantiles))

par(mfrow = c(2, 2))
plot(survfit(Surv(data.nswpcn$Time, data.nswpcn$DSD) ~ gg.groups.nswpcn), col = 1:(length(group_quantiles)))
plot(survfit(Surv(data.glasgow$Time, data.glasgow$DSD) ~ gg.groups.glasgow), col = 1:(length(group_quantiles)))
plot(survfit(Surv(data.nswpcn$Time, data.nswpcn$DSD) ~ cph.groups.nswpcn), col = 1:(length(group_quantiles)))
plot(survfit(Surv(data.glasgow$Time, data.glasgow$DSD) ~ cph.groups.glasgow), col = 1:(length(group_quantiles)))
```

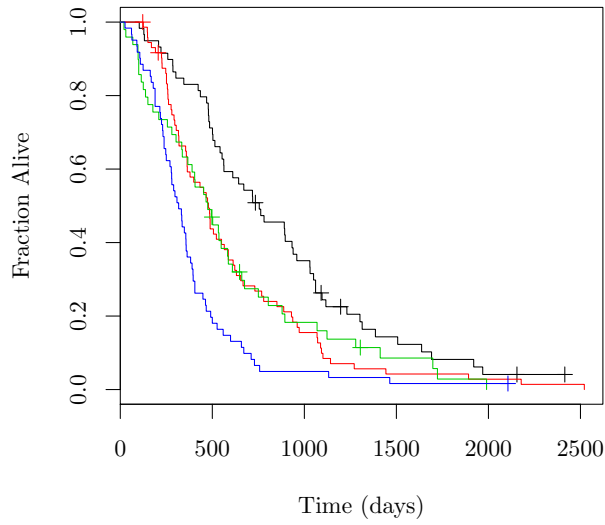
GG: NSWPCN (Resubstitution)



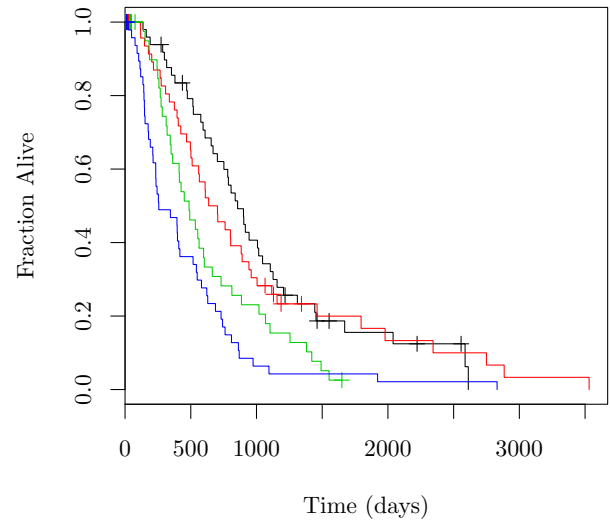
GG: Glasgow



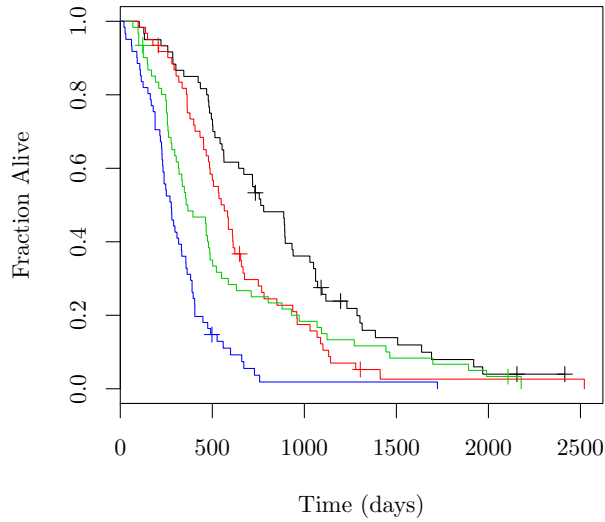
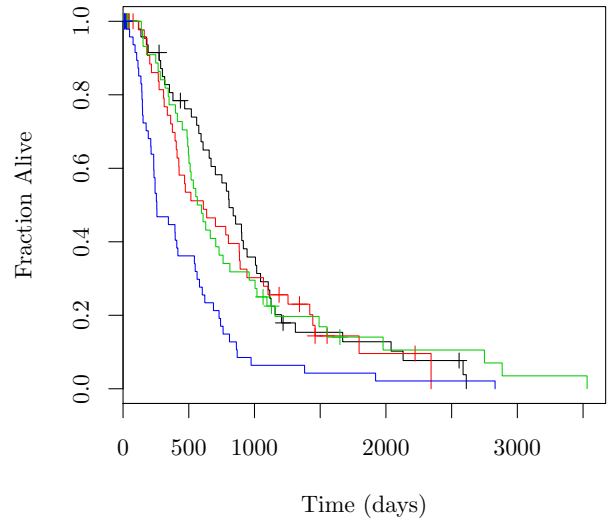
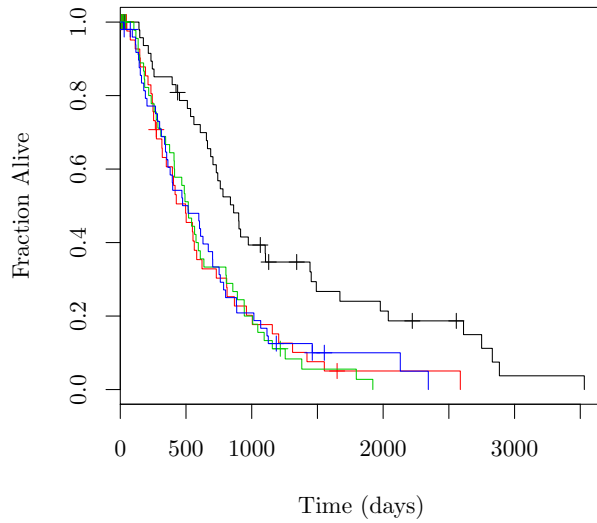
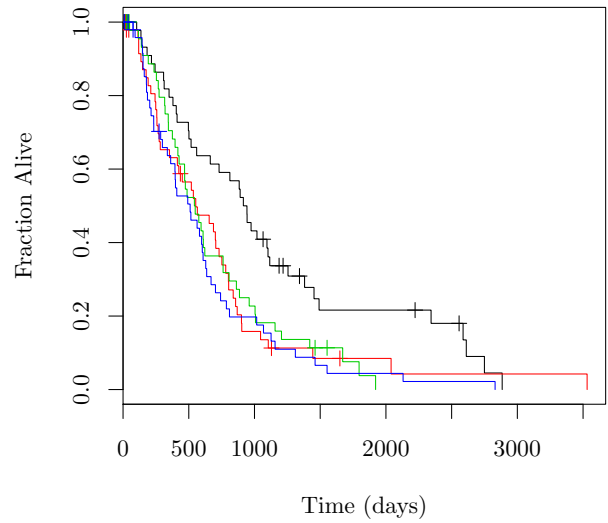
CPH: NSWPCN (Resubstitution)



CPH: Glasgow



```
plot(survfit(Surv(data.nswpcn$Time, data.nswpcn$DSD) ~ rsf.groups.nswpcn), col = 1:(length(group_quantil
plot(survfit(Surv(data.glasgow$Time, data.glasgow$DSD) ~ rsf.groups.glasgow), col = 1:(length(group_quar
plot(survfit(Surv(data.glasgow$Time, data.glasgow$DSD) ~ mskcc_pre.groups.glasgow), col = 1:(length(grou
plot(survfit(Surv(data.glasgow$Time, data.glasgow$DSD) ~ mskcc_post.groups.glasgow), col = 1:(length(grou
```

RSF: NSWPCN (Resubstitution)**RSF: Glasgow****MSKCC Preop: Glasgow****MSKCC Postop: Glasgow**

```
par(mfrow = c(1, 1))
```

```
# temp = survfit(Surv(data.nswpcnTime, data.nswpcnDSD) ~ gg.groups.nswpcn)
# plot(0 ~ 0, type = "n", xlim = c(0, max(data.nswpcnTime)), ylim = c(0, 1))
# for (i in )
```

Weird. MSKCC somehow is still finding a subgroup, and it's somehow even clearer in preop! This is based on an approximation to GG only, but should be pretty close. It certainly does OK on resubstituted data, but not so well on the Glasgow patients.

Decision curve analysis.

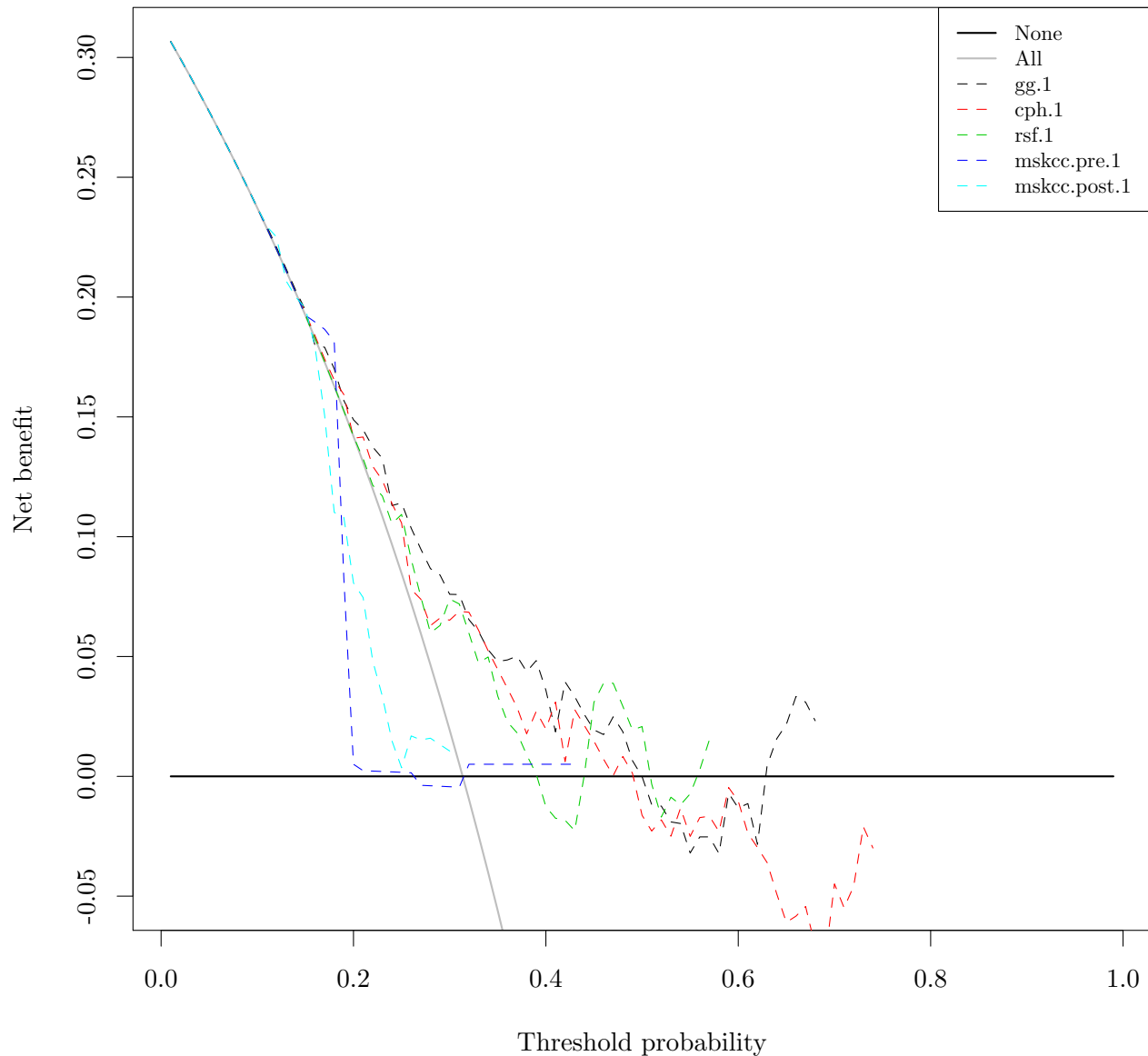
```
temp.data = data.frame(Time = data.glasgow$Time, DSD = data.glasgow$DSD*1,
  gg.1 = 1-gg.prob.glasgow[val.prob.times == 365,], gg.2 = 1-gg.prob.glasgow[val.prob.times == 365*2,],
  gg2.1 = 1-gg2.prob.glasgow[val.prob.times == 365,], gg2.2 = 1-gg2.prob.glasgow[val.prob.times == 365*2,])
```



```

cph.1 = 1-cph.prob.glasgow[val.prob.times == 365,], cph.2 = 1-cph.prob.glasgow[val.prob.times == 365,]
rsf.1 = 1-rsf.prob.glasgow[val.prob.times == 365,], rsf.2 = 1-rsf.prob.glasgow[val.prob.times == 365,]
mskcc.pre.1 = 1-mskcc_pre.12mo.glasgow, mskcc.pre.2 = 1-mskcc_pre.24mo.glasgow, mskcc.pre.3 = 1-mskcc_pre.36mo.glasgow
mskcc.post.1 = 1-mskcc_post.12mo.glasgow, mskcc.post.2 = 1-mskcc_post.24mo.glasgow, mskcc.post.3 = 1-mskcc_post.36mo.glasgow
stdca(data = temp.data, outcome = "DSD", ttoutcome = "Time", predictors = c("gg.1", "cph.1", "rsf.1", "mskcc.pre.1", "mskcc.post.1"))
## [1] "gg.1: No observations with risk greater than 69% that have followup through the timepoint selected"
## [2] "cph.1: No observations with risk greater than 75% that have followup through the timepoint selected"
## [3] "rsf.1: No observations with risk greater than 58% that have followup through the timepoint selected"
## [4] "mskcc.pre.1: No observations with risk greater than 44%, and therefore net benefit not calculable"
## [5] "mskcc.post.1: No observations with risk greater than 31% that have followup through the timepoint selected"

```



```

## $N
## [1] 198
##
## $predictors
##      predictor harm.applied probability

```

```

## 1      gg.1      0      TRUE
## 2      cph.1      0      TRUE
## 3      rsf.1      0      TRUE
## 4 mskcc.pre.1      0      TRUE
## 5 mskcc.post.1      0      TRUE
##
## $interventions.avoided.per
## [1] 100
##
## $net.benefit
##      threshold      all none      gg.1      cph.1      rsf.1 mskcc.pre.1
## 1      0.01  0.306589      0 3.066e-01 0.3065893 0.3065893 0.306589
## 2      0.02  0.299514      0 2.995e-01 0.2995137 0.2995137 0.299514
## 3      0.03  0.292292      0 2.923e-01 0.2922922 0.2922922 0.292292
## 4      0.04  0.284920      0 2.849e-01 0.2849202 0.2849202 0.284920
## 5      0.05  0.277393      0 2.774e-01 0.2773931 0.2773931 0.277393
## 6      0.06  0.269706      0 2.697e-01 0.2697058 0.2697058 0.269706
## 7      0.07  0.261853      0 2.619e-01 0.2618532 0.2618532 0.261853
## 8      0.08  0.253830      0 2.538e-01 0.2538298 0.2538298 0.253830
## 9      0.09  0.245630      0 2.456e-01 0.2456301 0.2456301 0.245630
## 10     0.10  0.237248      0 2.372e-01 0.2372483 0.2372483 0.237248
## 11     0.11  0.228678      0 2.295e-01 0.2286780 0.2286780 0.228678
## 12     0.12  0.219913      0 2.208e-01 0.2199130 0.2199130 0.219913
## 13     0.13  0.210946      0 2.119e-01 0.2109465 0.2109465 0.210946
## 14     0.14  0.201771      0 2.028e-01 0.2017714 0.2017714 0.201771
## 15     0.15  0.192381      0 1.945e-01 0.1934405 0.1923805 0.192381
## 16     0.16  0.182766      0 1.798e-01 0.1838987 0.1827660 0.189592
## 17     0.17  0.172920      0 1.791e-01 0.1741270 0.1729198 0.186558
## 18     0.18  0.162833      0 1.701e-01 0.1654025 0.1628335 0.181338
## 19     0.19  0.152498      0 1.568e-01 0.1593271 0.1524981 0.082587
## 20     0.20  0.141904      0 1.488e-01 0.1410995 0.1419043 0.005051
## 21     0.21  0.131042      0 1.446e-01 0.1416072 0.1325664 0.002365
## 22     0.22  0.119902      0 1.375e-01 0.1293876 0.1215102 0.002202
## 23     0.23  0.108472      0 1.327e-01 0.1235510 0.1169676 0.002033
## 24     0.24  0.096741      0 1.130e-01 0.1138131 0.1054344 0.001861
## 25     0.25  0.084698      0 1.141e-01 0.1057266 0.1092942 0.001684
## 26     0.26  0.072329      0 1.036e-01 0.0780081 0.0905894 0.001502
## 27     0.27  0.059621      0 9.483e-02 0.0739156 0.0749007 -0.003736
## 28     0.28  0.046560      0 8.667e-02 0.0628975 0.0598748 -0.003928
## 29     0.29  0.033132      0 8.399e-02 0.0660750 0.0629576 -0.004126
## 30     0.30  0.019319      0 7.595e-02 0.0651715 0.0740064 -0.004329
## 31     0.31  0.005106      0 7.587e-02 0.0688417 0.0719203 -0.004538
## 32     0.32 -0.009524      0 6.540e-02 0.0685007 0.0597343 0.005051
## 33     0.33 -0.024592      0 6.047e-02 0.0610051 0.0473221 0.005051
## 34     0.34 -0.040116      0 5.281e-02 0.0523853 0.0498159 0.005051
## 35     0.35 -0.056118      0 4.795e-02 0.0445666 0.0334745 0.005051
## 36     0.36 -0.072620      0 4.857e-02 0.0367386 0.0226912 0.005051
## 37     0.37 -0.089645      0 5.014e-02 0.0288241 0.0182025 0.005051
## 38     0.38 -0.107220      0 4.368e-02 0.0177695 0.0090016 0.005051
## 39     0.39 -0.125371      0 4.830e-02 0.0271126 0.0009429 0.005051
## 40     0.40 -0.144128      0 3.599e-02 0.0197362 -0.0126816 0.005051
## 41     0.41 -0.163520      0 1.855e-02 0.0309890 -0.0174713 0.005051
## 42     0.42 -0.183580      0 3.941e-02 0.0061253 -0.0183568 0.005051
## 43     0.43 -0.204345      0 3.327e-02 0.0278254 -0.0226650 0.005051

```

## 44	0.44	-0.225851	0	2.581e-02	0.0211855	0.0006950	NA
## 45	0.45	-0.248139	0	1.939e-02	0.0146837	0.0309291	NA
## 46	0.46	-0.271253	0	1.743e-02	0.0071510	0.0389076	NA
## 47	0.47	-0.295239	0	2.486e-02	0.0003295	0.0388449	NA
## 48	0.48	-0.320147	0	1.864e-02	0.0082860	0.0292435	NA
## 49	0.49	-0.346032	0	6.549e-03	0.0013034	0.0193760	NA
## 50	0.50	-0.372953	0	-8.981e-05	-0.0162376	0.0207632	NA
## 51	0.51	-0.400973	0	-1.181e-02	-0.0228177	-0.0031952	NA
## 52	0.52	-0.430160	0	-1.242e-02	-0.0181641	-0.0170004	NA
## 53	0.53	-0.460588	0	-1.902e-02	-0.0249980	-0.0087041	NA
## 54	0.54	-0.492340	0	-1.968e-02	-0.0132078	-0.0118577	NA
## 55	0.55	-0.525503	0	-3.199e-02	-0.0250408	-0.0072952	NA
## 56	0.56	-0.560174	0	-2.527e-02	-0.0172036	0.0027548	NA
## 57	0.57	-0.596457	0	-2.527e-02	-0.0166393	0.0152690	NA
## 58	0.58	-0.634468	0	-3.224e-02	-0.0230479	NA	NA
## 59	0.59	-0.674333	0	-7.076e-03	-0.0046638	NA	NA
## 60	0.60	-0.716191	0	-1.319e-02	-0.0103359	NA	NA
## 61	0.61	-0.760196	0	-1.137e-02	-0.0237749	NA	NA
## 62	0.62	-0.806517	0	-2.840e-02	-0.0297169	NA	NA
## 63	0.63	-0.855342	0	4.489e-03	-0.0359800	NA	NA
## 64	0.64	-0.906879	0	1.569e-02	-0.0490620	NA	NA
## 65	0.65	-0.961362	0	2.170e-02	-0.0609031	NA	NA
## 66	0.66	-1.019049	0	3.330e-02	-0.0583284	NA	NA
## 67	0.67	-1.080232	0	3.094e-02	-0.0543048	NA	NA
## 68	0.68	-1.145239	0	2.320e-02	-0.0710227	NA	NA
## 69	0.69	-1.214441	0	NA	-0.0773868	NA	NA
## 70	0.70	-1.288255	0	NA	-0.0448934	NA	NA
## 71	0.71	-1.367161	0	NA	-0.0548589	NA	NA
## 72	0.72	-1.451702	0	NA	-0.0458430	NA	NA
## 73	0.73	-1.542506	0	NA	-0.0210183	NA	NA
## 74	0.74	-1.640294	0	NA	-0.0299145	NA	NA
## 75	0.75	-1.745906	0	NA	NA	NA	NA
## 76	0.76	-1.860319	0	NA	NA	NA	NA
## 77	0.77	-1.984681	0	NA	NA	NA	NA
## 78	0.78	-2.120348	0	NA	NA	NA	NA
## 79	0.79	-2.268936	0	NA	NA	NA	NA
## 80	0.80	-2.432383	0	NA	NA	NA	NA
## 81	0.81	-2.613035	0	NA	NA	NA	NA
## 82	0.82	-2.813759	0	NA	NA	NA	NA
## 83	0.83	-3.038097	0	NA	NA	NA	NA
## 84	0.84	-3.290479	0	NA	NA	NA	NA
## 85	0.85	-3.576510	0	NA	NA	NA	NA
## 86	0.86	-3.903404	0	NA	NA	NA	NA
## 87	0.87	-4.280589	0	NA	NA	NA	NA
## 88	0.88	-4.720638	0	NA	NA	NA	NA
## 89	0.89	-5.240696	0	NA	NA	NA	NA
## 90	0.90	-5.864766	0	NA	NA	NA	NA
## 91	0.91	-6.627517	0	NA	NA	NA	NA
## 92	0.92	-7.580957	0	NA	NA	NA	NA
## 93	0.93	-8.806808	0	NA	NA	NA	NA
## 94	0.94	-10.441276	0	NA	NA	NA	NA
## 95	0.95	-12.729531	0	NA	NA	NA	NA
## 96	0.96	-16.161914	0	NA	NA	NA	NA
## 97	0.97	-21.882552	0	NA	NA	NA	NA

## 98	0.98	-33.323828	0	NA	NA	NA	NA
## 99	0.99	-67.647657	0	NA	NA	NA	NA
##	mskcc.post.1						
## 1	0.306589						
## 2	0.299514						
## 3	0.292292						
## 4	0.284920						
## 5	0.277393						
## 6	0.269706						
## 7	0.261853						
## 8	0.253830						
## 9	0.245630						
## 10	0.237248						
## 11	0.229463						
## 12	0.225051						
## 13	0.206737						
## 14	0.200009						
## 15	0.195373						
## 16	0.179161						
## 17	0.150617						
## 18	0.110140						
## 19	0.108100						
## 20	0.080708						
## 21	0.074611						
## 22	0.048221						
## 23	0.033413						
## 24	0.014784						
## 25	0.003573						
## 26	0.016870						
## 27	0.015221						
## 28	0.015917						
## 29	0.013231						
## 30	0.010582						
## 31	NA						
## 32	NA						
## 33	NA						
## 34	NA						
## 35	NA						
## 36	NA						
## 37	NA						
## 38	NA						
## 39	NA						
## 40	NA						
## 41	NA						
## 42	NA						
## 43	NA						
## 44	NA						
## 45	NA						
## 46	NA						
## 47	NA						
## 48	NA						
## 49	NA						
## 50	NA						
## 51	NA						

```

## 52      NA
## 53      NA
## 54      NA
## 55      NA
## 56      NA
## 57      NA
## 58      NA
## 59      NA
## 60      NA
## 61      NA
## 62      NA
## 63      NA
## 64      NA
## 65      NA
## 66      NA
## 67      NA
## 68      NA
## 69      NA
## 70      NA
## 71      NA
## 72      NA
## 73      NA
## 74      NA
## 75      NA
## 76      NA
## 77      NA
## 78      NA
## 79      NA
## 80      NA
## 81      NA
## 82      NA
## 83      NA
## 84      NA
## 85      NA
## 86      NA
## 87      NA
## 88      NA
## 89      NA
## 90      NA
## 91      NA
## 92      NA
## 93      NA
## 94      NA
## 95      NA
## 96      NA
## 97      NA
## 98      NA
## 99      NA
##
## $interventions.avoided
##      threshold      gg.1      cph.1      rsf.1 mskcc.pre.1 mskcc.post.1
## 1          0.01 0.0000 0.0000 0.0000          0.000          0.0000
## 2          0.02 0.0000 0.0000 0.0000          0.000          0.0000
## 3          0.03 0.0000 0.0000 0.0000          0.000          0.0000

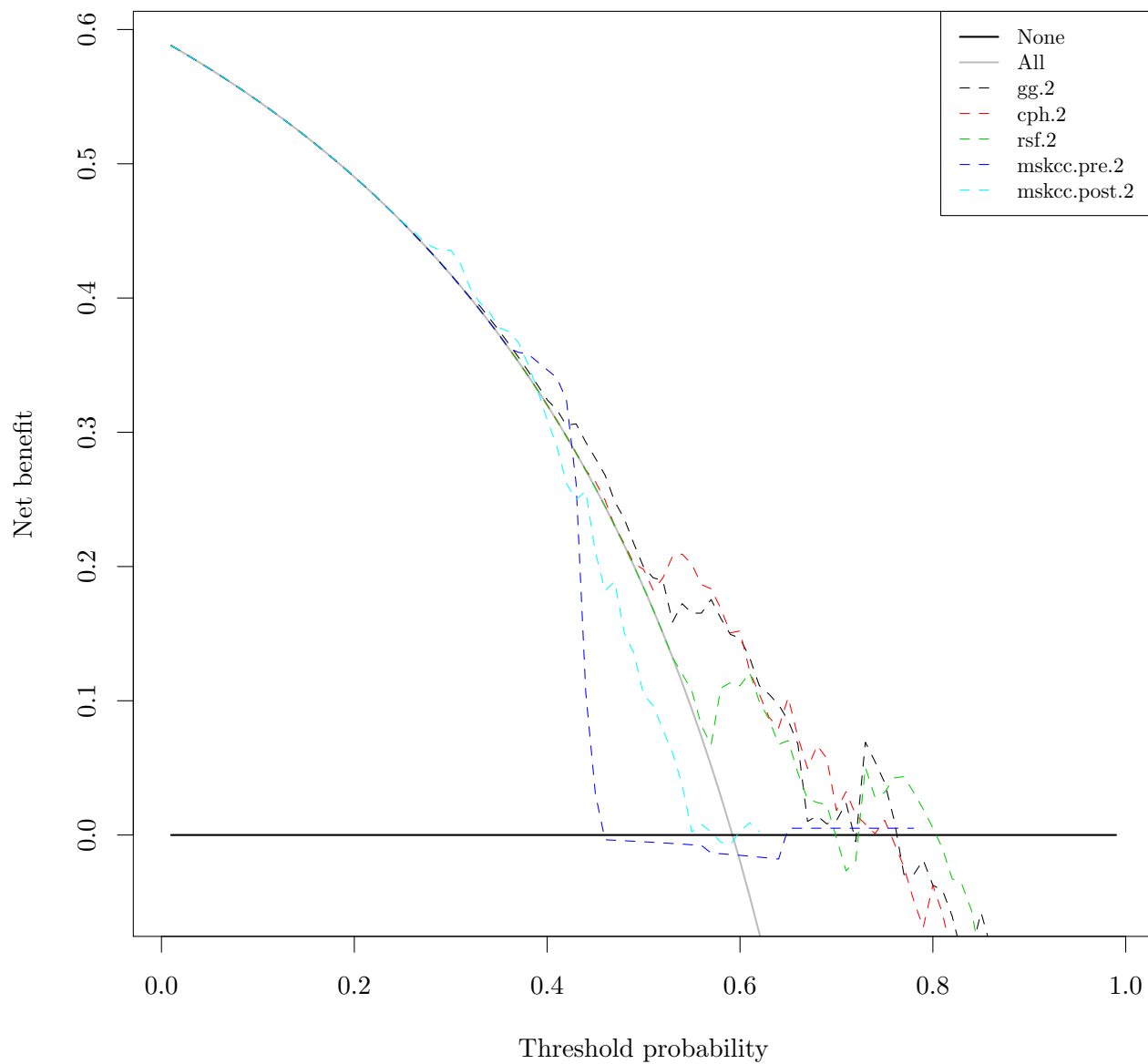
```

## 4	0.04	0.0000	0.0000	0.0000	0.000	0.0000
## 5	0.05	0.0000	0.0000	0.0000	0.000	0.0000
## 6	0.06	0.0000	0.0000	0.0000	0.000	0.0000
## 7	0.07	0.0000	0.0000	0.0000	0.000	0.0000
## 8	0.08	0.0000	0.0000	0.0000	0.000	0.0000
## 9	0.09	0.0000	0.0000	0.0000	0.000	0.0000
## 10	0.10	0.0000	0.0000	0.0000	0.000	0.0000
## 11	0.11	0.6354	0.0000	0.0000	0.000	0.6354
## 12	0.12	0.6246	0.0000	0.0000	0.000	3.7681
## 13	0.13	0.6154	0.0000	0.0000	0.000	-2.8173
## 14	0.14	0.6075	0.0000	0.0000	0.000	-1.0828
## 15	0.15	1.2024	0.6007	0.0000	0.000	1.6956
## 16	0.16	-1.5388	0.5947	0.0000	3.584	-1.8925
## 17	0.17	3.0082	0.5894	0.0000	6.659	-10.8891
## 18	0.18	3.2900	1.1704	0.0000	8.430	-24.0046
## 19	0.19	1.8332	2.9113	0.0000	-29.804	-18.9276
## 20	0.20	2.7580	-0.3219	0.0000	-54.742	-24.4785
## 21	0.21	5.1157	3.9744	0.5733	-48.407	-21.2290
## 22	0.22	6.2283	3.3632	0.5702	-41.730	-25.4140
## 23	0.23	8.1059	5.0482	2.8442	-35.634	-25.1286
## 24	0.24	5.1462	5.4060	2.7528	-30.046	-25.9530
## 25	0.25	8.8213	6.3086	7.3789	-24.904	-24.3376
## 26	0.26	8.8871	1.6164	5.1972	-20.159	-15.7845
## 27	0.27	9.5182	3.8648	4.1311	-17.130	-12.0046
## 28	0.28	10.3147	4.2010	3.4237	-12.983	-7.8798
## 29	0.29	12.4515	8.0655	7.3022	-9.122	-4.8722
## 30	0.30	13.2149	10.6989	12.7603	-5.518	-2.0387
## 31	0.31	15.7504	14.1862	14.8715	-2.147	NA
## 32	0.32	15.9210	16.5803	14.7175	3.097	NA
## 33	0.33	17.2692	17.3788	14.6007	6.018	NA
## 34	0.34	18.0387	17.9561	17.4574	8.768	NA
## 35	0.35	19.3266	18.6985	16.6386	11.360	NA
## 36	0.36	21.5449	19.4415	16.9441	13.808	NA
## 37	0.37	23.8021	20.1718	18.3633	16.124	NA
## 38	0.38	24.6206	20.3931	18.9625	18.318	NA
## 39	0.39	27.1646	23.8501	19.7569	20.399	NA
## 40	0.40	27.0174	24.5796	19.7169	22.377	NA
## 41	0.41	26.2010	27.9903	21.0167	24.258	NA
## 42	0.42	30.7932	26.1974	22.8166	26.049	NA
## 43	0.43	31.4983	30.7761	24.0831	27.757	NA
## 44	0.44	32.0290	31.4410	28.8331	NA	NA
## 45	0.45	32.6978	32.1228	34.1084	NA	NA
## 46	0.46	33.8888	32.6822	36.4101	NA	NA
## 47	0.47	36.0965	33.3300	37.6733	NA	NA
## 48	0.48	36.7018	35.5803	37.8507	NA	NA
## 49	0.49	36.6972	36.1513	38.0323	NA	NA
## 50	0.50	37.2863	35.6715	39.3716	NA	NA
## 51	0.51	37.3905	36.3325	38.2178	NA	NA
## 52	0.52	38.5610	38.0303	38.1378	NA	NA
## 53	0.53	39.1580	38.6278	40.0728	NA	NA
## 54	0.54	40.2634	40.8150	40.9300	NA	NA
## 55	0.55	40.3787	40.9470	42.3989	NA	NA
## 56	0.56	42.0282	42.6620	44.2301	NA	NA
## 57	0.57	43.0898	43.7406	46.1478	NA	NA

## 58	0.58	43.6095	44.2752	NA	NA	NA
## 59	0.59	46.3687	46.5363	NA	NA	NA
## 60	0.60	46.8669	47.0570	NA	NA	NA
## 61	0.61	47.8756	47.0827	NA	NA	NA
## 62	0.62	47.6908	47.6103	NA	NA	NA
## 63	0.63	50.4980	48.1213	NA	NA	NA
## 64	0.64	51.8947	48.2522	NA	NA	NA
## 65	0.65	52.9340	48.4862	NA	NA	NA
## 66	0.66	54.2120	49.4917	NA	NA	NA
## 67	0.67	54.7296	50.5307	NA	NA	NA
## 68	0.68	54.9854	50.5514	NA	NA	NA
## 69	0.69	NA	51.0850	NA	NA	NA
## 70	0.70	NA	53.2869	NA	NA	NA
## 71	0.71	NA	53.6011	NA	NA	NA
## 72	0.72	NA	54.6723	NA	NA	NA
## 73	0.73	NA	56.2742	NA	NA	NA
## 74	0.74	NA	56.5809	NA	NA	NA
## 75	0.75	NA	NA	NA	NA	NA
## 76	0.76	NA	NA	NA	NA	NA
## 77	0.77	NA	NA	NA	NA	NA
## 78	0.78	NA	NA	NA	NA	NA
## 79	0.79	NA	NA	NA	NA	NA
## 80	0.80	NA	NA	NA	NA	NA
## 81	0.81	NA	NA	NA	NA	NA
## 82	0.82	NA	NA	NA	NA	NA
## 83	0.83	NA	NA	NA	NA	NA
## 84	0.84	NA	NA	NA	NA	NA
## 85	0.85	NA	NA	NA	NA	NA
## 86	0.86	NA	NA	NA	NA	NA
## 87	0.87	NA	NA	NA	NA	NA
## 88	0.88	NA	NA	NA	NA	NA
## 89	0.89	NA	NA	NA	NA	NA
## 90	0.90	NA	NA	NA	NA	NA
## 91	0.91	NA	NA	NA	NA	NA
## 92	0.92	NA	NA	NA	NA	NA
## 93	0.93	NA	NA	NA	NA	NA
## 94	0.94	NA	NA	NA	NA	NA
## 95	0.95	NA	NA	NA	NA	NA
## 96	0.96	NA	NA	NA	NA	NA
## 97	0.97	NA	NA	NA	NA	NA
## 98	0.98	NA	NA	NA	NA	NA
## 99	0.99	NA	NA	NA	NA	NA

```
stdca(data = temp.data, outcome = "DSD", ttoutcome = "Time", predictors = c("gg.2", "cph.2", "rsf.2", "m
```

```
## [1] "gg.2: No observations with risk greater than 98% that have followup through the timepoint select
## [2] "cph.2: No observations with risk greater than 98% that have followup through the timepoint sele
## [3] "rsf.2: No observations with risk greater than 89%, and therefore net benefit not calculable in t
## [4] "mskcc.pre.2: No observations with risk greater than 79%, and therefore net benefit not calculabl
## [5] "mskcc.post.2: No observations with risk greater than 63% that have followup through the timepoir
```



```
## $N
## [1] 198
##
## $predictors
##      predictor harm.applied probability
## 1      gg.2      0      TRUE
## 2      cph.2      0      TRUE
## 3      rsf.2      0      TRUE
## 4 mskcc.pre.2      0      TRUE
## 5 mskcc.post.2     0      TRUE
##
## $interventions.avoided.per
## [1] 100
##
## $net.benefit
##      threshold      all none      gg.2      cph.2      rsf.2 mskcc.pre.2
## 1      0.01  0.588071  0  0.588071  0.5880714  0.588071  0.588071
```


## 2	0.02	0.583868	0	0.583868	0.5838680	0.583868	0.583868
## 3	0.03	0.579578	0	0.579578	0.5795780	0.579578	0.579578
## 4	0.04	0.575199	0	0.575199	0.5751986	0.575199	0.575199
## 5	0.05	0.570727	0	0.570727	0.5707270	0.570727	0.570727
## 6	0.06	0.566160	0	0.566160	0.5661603	0.566160	0.566160
## 7	0.07	0.561495	0	0.561495	0.5614953	0.561495	0.561495
## 8	0.08	0.556729	0	0.556729	0.5567290	0.556729	0.556729
## 9	0.09	0.551858	0	0.551858	0.5518578	0.551858	0.551858
## 10	0.10	0.546878	0	0.546878	0.5468785	0.546878	0.546878
## 11	0.11	0.541787	0	0.541787	0.5417872	0.541787	0.541787
## 12	0.12	0.536580	0	0.536580	0.5365803	0.536580	0.536580
## 13	0.13	0.531254	0	0.531254	0.5312536	0.531254	0.531254
## 14	0.14	0.525803	0	0.525803	0.5258031	0.525803	0.525803
## 15	0.15	0.520224	0	0.520224	0.5202243	0.520224	0.520224
## 16	0.16	0.514513	0	0.514513	0.5145127	0.514513	0.514513
## 17	0.17	0.508663	0	0.508663	0.5086634	0.508663	0.508663
## 18	0.18	0.502672	0	0.502672	0.5026715	0.502672	0.502672
## 19	0.19	0.496532	0	0.496532	0.4965317	0.496532	0.496532
## 20	0.20	0.490238	0	0.490238	0.4902383	0.490238	0.490238
## 21	0.21	0.483786	0	0.483786	0.4837856	0.483786	0.483786
## 22	0.22	0.477167	0	0.477167	0.4771675	0.477167	0.477167
## 23	0.23	0.470377	0	0.470377	0.4703775	0.470377	0.470377
## 24	0.24	0.463409	0	0.463409	0.4634087	0.463409	0.463409
## 25	0.25	0.456254	0	0.456254	0.4562542	0.456254	0.456254
## 26	0.26	0.448906	0	0.448906	0.4489063	0.448906	0.448906
## 27	0.27	0.441357	0	0.441357	0.4413570	0.441357	0.441357
## 28	0.28	0.433598	0	0.433598	0.4335981	0.433598	0.433598
## 29	0.29	0.425621	0	0.425621	0.4256206	0.425621	0.425621
## 30	0.30	0.417415	0	0.417415	0.4174152	0.417415	0.417415
## 31	0.31	0.408972	0	0.408972	0.4089719	0.408972	0.408972
## 32	0.32	0.400280	0	0.400280	0.4002804	0.400280	0.400280
## 33	0.33	0.391329	0	0.394265	0.3913293	0.391329	0.391329
## 34	0.34	0.382107	0	0.385164	0.3821070	0.382107	0.382107
## 35	0.35	0.372601	0	0.375783	0.3726010	0.372601	0.372601
## 36	0.36	0.362798	0	0.366108	0.3627979	0.362798	0.362798
## 37	0.37	0.352684	0	0.356127	0.3526836	0.352684	0.359576
## 38	0.38	0.342243	0	0.345823	0.3422430	0.342243	0.358381
## 39	0.39	0.331460	0	0.335182	0.3314601	0.331460	0.352422
## 40	0.40	0.320318	0	0.324186	0.3203177	0.320318	0.346536
## 41	0.41	0.308798	0	0.316842	0.3087977	0.308798	0.340628
## 42	0.42	0.296880	0	0.305237	0.2968804	0.296880	0.323984
## 43	0.43	0.284545	0	0.306295	0.2845450	0.284545	0.261932
## 44	0.44	0.271769	0	0.292657	0.2717690	0.271769	0.106312
## 45	0.45	0.258528	0	0.280623	0.2632071	0.258528	0.030762
## 46	0.46	0.244797	0	0.268143	0.2496563	0.244797	-0.003554
## 47	0.47	0.230548	0	0.248463	0.2298125	0.230548	-0.003907
## 48	0.48	0.215751	0	0.235564	0.2169548	0.215751	-0.004274
## 49	0.49	0.200374	0	0.216786	0.2020961	0.200374	-0.004654
## 50	0.50	0.184381	0	0.199590	0.1979246	0.184381	-0.005051
## 51	0.51	0.167736	0	0.191570	0.1822772	0.167736	-0.005463
## 52	0.52	0.150397	0	0.189628	0.1914811	0.150397	-0.005892
## 53	0.53	0.132321	0	0.158620	0.2075295	0.132321	-0.006340
## 54	0.54	0.113458	0	0.172338	0.2092613	0.120040	-0.006807
## 55	0.55	0.093757	0	0.165249	0.2016539	0.107446	-0.007295

## 56	0.56	0.073161	0	0.165299	0.1865321	0.081457	-0.007805
## 57	0.57	0.051606	0	0.175484	0.1834252	0.067168	-0.013390
## 58	0.58	0.029025	0	0.161504	0.1687929	0.109337	-0.013949
## 59	0.59	0.005343	0	0.149410	0.1506160	0.113494	-0.014536
## 60	0.60	-0.019523	0	0.146603	0.1519405	0.111146	-0.015152
## 61	0.61	-0.045665	0	0.132102	0.1219518	0.121122	-0.015799
## 62	0.62	-0.073183	0	0.111276	0.1049051	0.099386	-0.016481
## 63	0.63	-0.102187	0	0.104899	0.0878113	0.086335	-0.017199
## 64	0.64	-0.132804	0	0.097075	0.0797604	0.067576	-0.017957
## 65	0.65	-0.165170	0	0.085143	0.1024069	0.070268	0.005051
## 66	0.66	-0.199439	0	0.067742	0.0731230	0.046247	0.005051
## 67	0.67	-0.235786	0	0.010112	0.0495696	0.026681	0.005051
## 68	0.68	-0.274404	0	0.014298	0.0667518	0.024238	0.005051
## 69	0.69	-0.315514	0	0.008267	0.0570675	0.022454	0.005051
## 70	0.70	-0.359365	0	0.010728	0.0183144	-0.002186	0.005051
## 71	0.71	-0.406239	0	0.023764	0.0323611	-0.026743	0.005051
## 72	0.72	-0.456462	0	-0.005057	0.0149382	-0.019112	0.005051
## 73	0.73	-0.510405	0	0.069085	0.0081694	0.050416	0.005051
## 74	0.74	-0.568498	0	0.054648	0.0009491	0.028083	0.005051
## 75	0.75	-0.631237	0	0.039056	0.0109565	0.031769	0.005051
## 76	0.76	-0.699206	0	0.010737	-0.0060533	0.042494	0.005051
## 77	0.77	-0.773084	0	-0.029448	-0.0238759	0.043494	0.005051
## 78	0.78	-0.853679	0	-0.029554	-0.0485375	0.031926	0.005051
## 79	0.79	-0.941949	0	-0.018673	-0.0688796	0.019257	NA
## 80	0.80	-1.039047	0	-0.037433	-0.0374332	0.005321	NA
## 81	0.81	-1.146365	0	-0.041161	-0.0585421	-0.010082	NA
## 82	0.82	-1.265608	0	-0.060394	-0.0902927	-0.032548	NA
## 83	0.83	-1.398879	0	-0.088730	-0.0887304	-0.036450	NA
## 84	0.84	-1.548808	0	-0.086287	-0.0862866	-0.056090	NA
## 85	0.85	-1.718729	0	-0.057720	-0.1132512	-0.094688	NA
## 86	0.86	-1.912924	0	-0.083488	-0.1496243	-0.123256	NA
## 87	0.87	-2.136995	0	-0.135557	-0.1852209	-0.180579	NA
## 88	0.88	-2.398411	0	-0.130648	-0.2230930	-0.117845	NA
## 89	0.89	-2.707358	0	-0.090160	-0.2713815	NA	NA
## 90	0.90	-3.078094	0	-0.105246	-0.2873377	NA	NA
## 91	0.91	-3.531215	0	-0.160244	-0.3157645	NA	NA
## 92	0.92	-4.097617	0	-0.212121	-0.4073387	NA	NA
## 93	0.93	-4.825848	0	-0.179936	-0.4156983	NA	NA
## 94	0.94	-5.796823	0	-0.247475	-0.2696153	NA	NA
## 95	0.95	-7.156187	0	-0.324296	-0.3063973	NA	NA
## 96	0.96	-9.195234	0	-0.181818	-0.1824495	NA	NA
## 97	0.97	-12.593645	0	-0.117845	-0.1230487	NA	NA
## 98	0.98	-19.390468	0	NA	NA	NA	NA
## 99	0.99	-39.780936	0	NA	NA	NA	NA
##	mskcc.post.2						
## 1	0.588071						
## 2	0.583868						
## 3	0.579578						
## 4	0.575199						
## 5	0.570727						
## 6	0.566160						
## 7	0.561495						
## 8	0.556729						
## 9	0.551858						

## 10	0.546878
## 11	0.541787
## 12	0.536580
## 13	0.531254
## 14	0.525803
## 15	0.520224
## 16	0.514513
## 17	0.508663
## 18	0.502672
## 19	0.496532
## 20	0.490238
## 21	0.483786
## 22	0.477167
## 23	0.470377
## 24	0.463409
## 25	0.456254
## 26	0.451087
## 27	0.443637
## 28	0.438366
## 29	0.435596
## 30	0.435683
## 31	0.425530
## 32	0.407691
## 33	0.396793
## 34	0.389643
## 35	0.377965
## 36	0.375035
## 37	0.367111
## 38	0.351077
## 39	0.331653
## 40	0.309274
## 41	0.289669
## 42	0.261943
## 43	0.249775
## 44	0.256111
## 45	0.210665
## 46	0.182000
## 47	0.188886
## 48	0.150492
## 49	0.135305
## 50	0.104494
## 51	0.096397
## 52	0.078417
## 53	0.061267
## 54	0.037378
## 55	0.002300
## 56	0.007896
## 57	0.002349
## 58	-0.005400
## 59	-0.007133
## 60	0.002841
## 61	0.009065
## 62	0.002481
## 63	NA

```

## 64      NA
## 65      NA
## 66      NA
## 67      NA
## 68      NA
## 69      NA
## 70      NA
## 71      NA
## 72      NA
## 73      NA
## 74      NA
## 75      NA
## 76      NA
## 77      NA
## 78      NA
## 79      NA
## 80      NA
## 81      NA
## 82      NA
## 83      NA
## 84      NA
## 85      NA
## 86      NA
## 87      NA
## 88      NA
## 89      NA
## 90      NA
## 91      NA
## 92      NA
## 93      NA
## 94      NA
## 95      NA
## 96      NA
## 97      NA
## 98      NA
## 99      NA
##
## $interventions.avoided
##      threshold      gg.2      cph.2      rsf.2 mskcc.pre.2 mskcc.post.2
## 1          0.01 0.0000 0.00000 0.0000      0.0000      0.00000
## 2          0.02 0.0000 0.00000 0.0000      0.0000      0.00000
## 3          0.03 0.0000 0.00000 0.0000      0.0000      0.00000
## 4          0.04 0.0000 0.00000 0.0000      0.0000      0.00000
## 5          0.05 0.0000 0.00000 0.0000      0.0000      0.00000
## 6          0.06 0.0000 0.00000 0.0000      0.0000      0.00000
## 7          0.07 0.0000 0.00000 0.0000      0.0000      0.00000
## 8          0.08 0.0000 0.00000 0.0000      0.0000      0.00000
## 9          0.09 0.0000 0.00000 0.0000      0.0000      0.00000
## 10         0.10 0.0000 0.00000 0.0000      0.0000      0.00000
## 11         0.11 0.0000 0.00000 0.0000      0.0000      0.00000
## 12         0.12 0.0000 0.00000 0.0000      0.0000      0.00000
## 13         0.13 0.0000 0.00000 0.0000      0.0000      0.00000
## 14         0.14 0.0000 0.00000 0.0000      0.0000      0.00000
## 15         0.15 0.0000 0.00000 0.0000      0.0000      0.00000

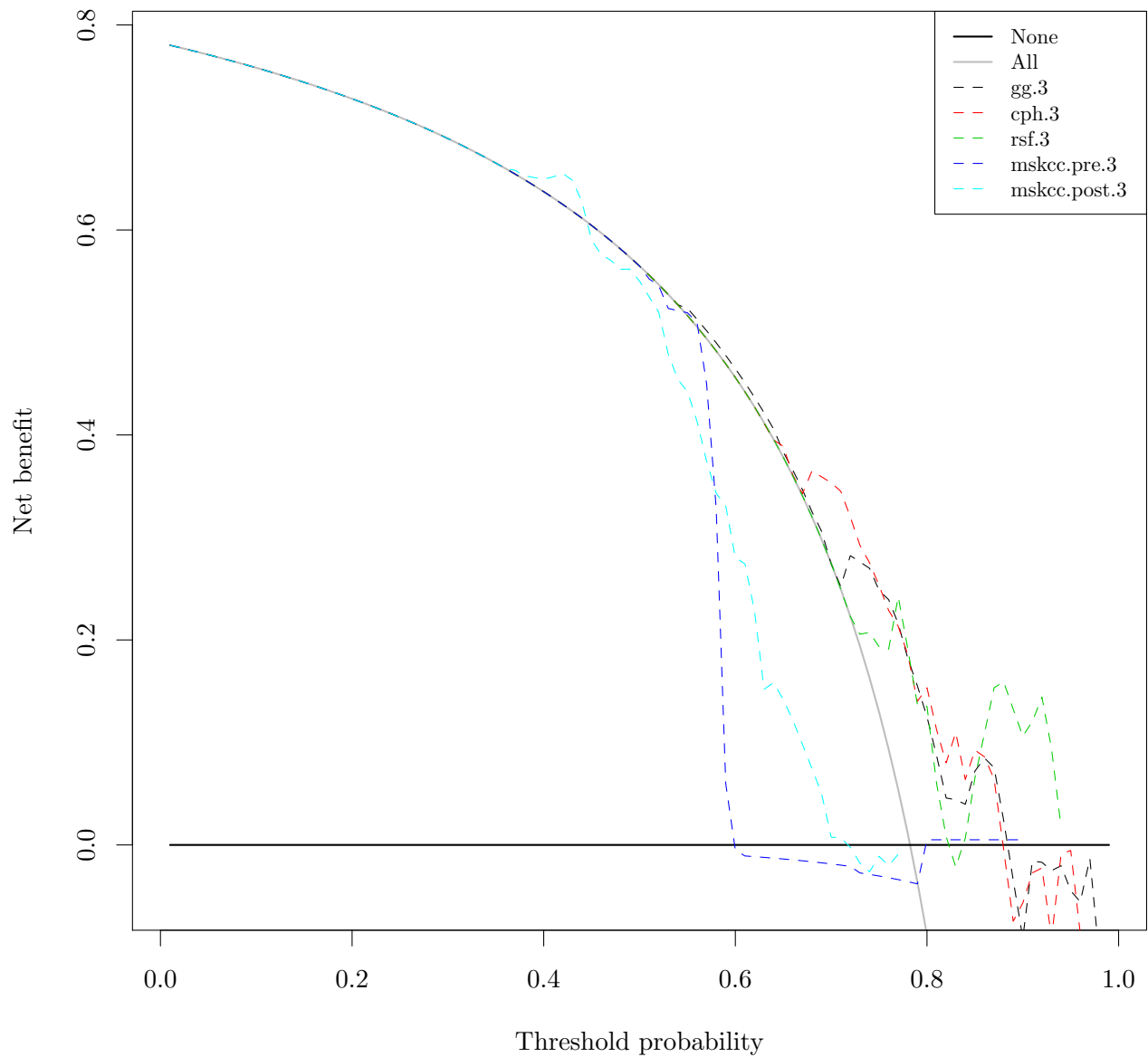
```

## 16	0.16	0.0000	0.00000	0.0000	0.0000	0.00000
## 17	0.17	0.0000	0.00000	0.0000	0.0000	0.00000
## 18	0.18	0.0000	0.00000	0.0000	0.0000	0.00000
## 19	0.19	0.0000	0.00000	0.0000	0.0000	0.00000
## 20	0.20	0.0000	0.00000	0.0000	0.0000	0.00000
## 21	0.21	0.0000	0.00000	0.0000	0.0000	0.00000
## 22	0.22	0.0000	0.00000	0.0000	0.0000	0.00000
## 23	0.23	0.0000	0.00000	0.0000	0.0000	0.00000
## 24	0.24	0.0000	0.00000	0.0000	0.0000	0.00000
## 25	0.25	0.0000	0.00000	0.0000	0.0000	0.00000
## 26	0.26	0.0000	0.00000	0.0000	0.0000	0.62065
## 27	0.27	0.0000	0.00000	0.0000	0.0000	0.61636
## 28	0.28	0.0000	0.00000	0.0000	0.0000	1.22606
## 29	0.29	0.0000	0.00000	0.0000	0.0000	2.44225
## 30	0.30	0.0000	0.00000	0.0000	0.0000	4.26248
## 31	0.31	0.0000	0.00000	0.0000	0.0000	3.68553
## 32	0.32	0.0000	0.00000	0.0000	0.0000	1.57477
## 33	0.33	0.5961	0.00000	0.0000	0.0000	1.10936
## 34	0.34	0.5934	0.00000	0.0000	0.0000	1.46295
## 35	0.35	0.5909	0.00000	0.0000	0.0000	0.99618
## 36	0.36	0.5885	0.00000	0.0000	0.0000	2.17543
## 37	0.37	0.5863	0.00000	0.0000	1.1735	2.45650
## 38	0.38	0.5841	0.00000	0.0000	2.6330	1.44129
## 39	0.39	0.5821	0.00000	0.0000	3.2787	0.03024
## 40	0.40	0.5802	0.00000	0.0000	3.9327	-1.65649
## 41	0.41	1.1576	0.00000	0.0000	4.5804	-2.75266
## 42	0.42	1.1541	0.00000	0.0000	3.7429	-4.82473
## 43	0.43	2.8832	0.00000	0.0000	-2.9976	-4.60908
## 44	0.44	2.6585	0.00000	0.0000	-21.0582	-1.99279
## 45	0.45	2.7004	0.57184	0.0000	-27.8381	-5.84997
## 46	0.46	2.7405	0.57039	0.0000	-29.1543	-7.37192
## 47	0.47	2.0201	-0.08298	0.0000	-26.4386	-4.69812
## 48	0.48	2.1464	0.13038	0.0000	-23.8360	-7.06973
## 49	0.49	1.7082	0.17926	0.0000	-21.3397	-6.77248
## 50	0.50	1.5208	1.35433	0.0000	-18.9432	-7.98875
## 51	0.51	2.2899	1.39710	0.0000	-16.6407	-6.85411
## 52	0.52	3.6213	3.79236	0.0000	-14.4267	-6.64428
## 53	0.53	2.3323	6.66947	0.0000	-12.2963	-6.30094
## 54	0.54	5.0157	8.16103	0.5607	-10.2448	-6.48092
## 55	0.55	5.8494	8.82793	1.1200	-8.2679	-7.48287
## 56	0.56	7.2395	8.90776	0.6518	-6.3616	-5.12797
## 57	0.57	9.3451	9.94424	1.1739	-4.9032	-3.71588
## 58	0.58	9.5933	10.12110	5.8157	-3.1119	-2.49289
## 59	0.59	10.0114	10.09524	7.5156	-1.3814	-0.86701
## 60	0.60	11.0751	11.43092	8.7113	0.2915	1.49095
## 61	0.61	11.3654	10.71649	10.6634	1.9095	3.49913
## 62	0.62	11.3055	10.91505	10.5768	3.4753	4.63744
## 63	0.63	12.1622	11.15866	11.0719	4.9914	NA
## 64	0.64	12.9307	11.95673	11.2714	6.4601	NA
## 65	0.65	13.4783	14.40797	12.6774	9.1657	NA
## 66	0.66	13.7639	14.04109	12.6566	10.5343	NA
## 67	0.67	12.1114	14.05482	12.9275	11.8621	NA
## 68	0.68	13.5860	16.05440	14.0538	13.1508	NA
## 69	0.69	14.5467	16.73917	15.1841	14.4022	NA

## 70	0.70	15.8611	16.18624	15.3076	15.6178	NA
## 71	0.71	17.5635	17.91466	15.5006	16.7992	NA
## 72	0.72	17.5546	18.33223	17.0081	17.9477	NA
## 73	0.73	21.4332	19.18015	20.7427	19.0648	NA
## 74	0.74	21.8943	20.00758	20.9609	20.1517	NA
## 75	0.75	22.3431	21.40646	22.1002	21.2096	NA
## 76	0.76	22.4192	21.88902	23.4221	22.2397	NA
## 77	0.77	22.2125	22.37895	24.3913	23.2430	NA
## 78	0.78	23.2445	22.70912	24.9786	24.2206	NA
## 79	0.79	24.5428	23.20818	25.5511	NA	NA
## 80	0.80	25.0403	25.04034	26.1092	NA	NA
## 81	0.81	25.9245	25.51683	26.6536	NA	NA
## 82	0.82	26.4559	25.79959	27.0672	NA	NA
## 83	0.83	26.8344	26.83436	27.9052	NA	NA
## 84	0.84	27.8576	27.85756	28.4327	NA	NA
## 85	0.85	29.3119	28.33196	28.6595	NA	NA
## 86	0.86	29.7815	28.70488	29.1341	NA	NA
## 87	0.87	29.9065	29.16444	29.2338	NA	NA
## 88	0.88	30.9241	29.66343	31.0986	NA	NA
## 89	0.89	32.3474	30.10757	NA	NA	NA
## 90	0.90	33.0316	31.00840	NA	NA	NA
## 91	0.91	33.3393	31.80116	NA	NA	NA
## 92	0.92	33.7869	32.08938	NA	NA	NA
## 93	0.93	34.9692	33.19467	NA	NA	NA
## 94	0.94	35.4214	35.28005	NA	NA	NA
## 95	0.95	35.9573	36.05153	NA	NA	NA
## 96	0.96	37.5559	37.55327	NA	NA	NA
## 97	0.97	38.5849	38.56886	NA	NA	NA
## 98	0.98	NA	NA	NA	NA	NA
## 99	0.99	NA	NA	NA	NA	NA

```
stdca(data = temp.data, outcome = "DSD", ttoutcome = "Time", predictors = c("gg.3", "cph.3", "rsf.3", "m

## [1] "rsf.3: No observations with risk greater than 95% that have followup through the timepoint sele
## [2] "mskcc.pre.3: No observations with risk greater than 91%, and therefore net benefit not calculabl
## [3] "mskcc.post.3: No observations with risk greater than 78% that have followup through the timepoir
```



```
## $N
## [1] 198
##
## $predictors
##      predictor harm.applied probability
## 1      gg.3      0      TRUE
## 2      cph.3      0      TRUE
## 3      rsf.3      0      TRUE
## 4 mskcc.pre.3      0      TRUE
## 5 mskcc.post.3     0      TRUE
##
## $interventions.avoided.per
## [1] 100
##
## $net.benefit
##      threshold      all none      gg.3      cph.3      rsf.3 mskcc.pre.3
## 1      0.01    0.78021    0    0.78021    0.780211    0.780211    0.780211
```

## 2	0.02	0.77797	0	0.77797	0.777968	0.777968	0.777968
## 3	0.03	0.77568	0	0.77568	0.775679	0.775679	0.775679
## 4	0.04	0.77334	0	0.77334	0.773342	0.773342	0.773342
## 5	0.05	0.77096	0	0.77096	0.770956	0.770956	0.770956
## 6	0.06	0.76852	0	0.76852	0.768520	0.768520	0.768520
## 7	0.07	0.76603	0	0.76603	0.766031	0.766031	0.766031
## 8	0.08	0.76349	0	0.76349	0.763488	0.763488	0.763488
## 9	0.09	0.76089	0	0.76089	0.760889	0.760889	0.760889
## 10	0.10	0.75823	0	0.75823	0.758232	0.758232	0.758232
## 11	0.11	0.75552	0	0.75552	0.755515	0.755515	0.755515
## 12	0.12	0.75274	0	0.75274	0.752737	0.752737	0.752737
## 13	0.13	0.74989	0	0.74989	0.749895	0.749895	0.749895
## 14	0.14	0.74699	0	0.74699	0.746987	0.746987	0.746987
## 15	0.15	0.74401	0	0.74401	0.744010	0.744010	0.744010
## 16	0.16	0.74096	0	0.74096	0.740963	0.740963	0.740963
## 17	0.17	0.73784	0	0.73784	0.737842	0.737842	0.737842
## 18	0.18	0.73464	0	0.73464	0.734645	0.734645	0.734645
## 19	0.19	0.73137	0	0.73137	0.731369	0.731369	0.731369
## 20	0.20	0.72801	0	0.72801	0.728011	0.728011	0.728011
## 21	0.21	0.72457	0	0.72457	0.724568	0.724568	0.724568
## 22	0.22	0.72104	0	0.72104	0.721037	0.721037	0.721037
## 23	0.23	0.71741	0	0.71741	0.717414	0.717414	0.717414
## 24	0.24	0.71370	0	0.71370	0.713695	0.713695	0.713695
## 25	0.25	0.70988	0	0.70988	0.709878	0.709878	0.709878
## 26	0.26	0.70596	0	0.70596	0.705958	0.705958	0.705958
## 27	0.27	0.70193	0	0.70193	0.701930	0.701930	0.701930
## 28	0.28	0.69779	0	0.69779	0.697790	0.697790	0.697790
## 29	0.29	0.69353	0	0.69353	0.693533	0.693533	0.693533
## 30	0.30	0.68916	0	0.68916	0.689155	0.689155	0.689155
## 31	0.31	0.68465	0	0.68465	0.684650	0.684650	0.684650
## 32	0.32	0.68001	0	0.68001	0.680013	0.680013	0.680013
## 33	0.33	0.67524	0	0.67524	0.675237	0.675237	0.675237
## 34	0.34	0.67032	0	0.67032	0.670316	0.670316	0.670316
## 35	0.35	0.66524	0	0.66524	0.665244	0.665244	0.665244
## 36	0.36	0.66001	0	0.66001	0.660013	0.660013	0.660013
## 37	0.37	0.65462	0	0.65462	0.654617	0.654617	0.654617
## 38	0.38	0.64905	0	0.64905	0.649046	0.649046	0.649046
## 39	0.39	0.64329	0	0.64329	0.643293	0.643293	0.643293
## 40	0.40	0.63735	0	0.63735	0.637348	0.637348	0.637348
## 41	0.41	0.63120	0	0.63120	0.631201	0.631201	0.631201
## 42	0.42	0.62484	0	0.62484	0.624842	0.624842	0.624842
## 43	0.43	0.61826	0	0.61826	0.618261	0.618261	0.618261
## 44	0.44	0.61144	0	0.61144	0.611444	0.611444	0.611444
## 45	0.45	0.60438	0	0.60438	0.604379	0.604379	0.604379
## 46	0.46	0.59705	0	0.59705	0.597053	0.597053	0.597053
## 47	0.47	0.58945	0	0.58945	0.589450	0.589450	0.589450
## 48	0.48	0.58155	0	0.58155	0.581555	0.581555	0.581555
## 49	0.49	0.57335	0	0.57335	0.573350	0.573350	0.573350
## 50	0.50	0.56482	0	0.56482	0.564817	0.564817	0.564817
## 51	0.51	0.55594	0	0.55594	0.555936	0.555936	0.552251
## 52	0.52	0.54668	0	0.54668	0.546685	0.546685	0.545592
## 53	0.53	0.53704	0	0.53704	0.537040	0.537040	0.523438
## 54	0.54	0.52698	0	0.52698	0.526975	0.526975	0.521261
## 55	0.55	0.51646	0	0.52357	0.516463	0.516463	0.519226

## 56	0.56	0.50547	0	0.51285	0.505474	0.505474	0.509906
## 57	0.57	0.49397	0	0.50164	0.493973	0.493973	0.450034
## 58	0.58	0.48193	0	0.48990	0.481925	0.481925	0.328353
## 59	0.59	0.46929	0	0.47758	0.469289	0.469289	0.059611
## 60	0.60	0.45602	0	0.46464	0.456021	0.456021	-0.005051
## 61	0.61	0.44207	0	0.45105	0.442073	0.442073	-0.010749
## 62	0.62	0.42739	0	0.43673	0.427391	0.427391	-0.011430
## 63	0.63	0.41192	0	0.42165	0.410991	0.411915	-0.012149
## 64	0.64	0.39558	0	0.40572	0.395059	0.395579	-0.012907
## 65	0.65	0.37831	0	0.38348	0.388865	0.378310	-0.013709
## 66	0.66	0.36003	0	0.36564	0.360888	0.360025	-0.014557
## 67	0.67	0.34063	0	0.34672	0.342592	0.340632	-0.015458
## 68	0.68	0.32003	0	0.32506	0.365005	0.320027	-0.016414
## 69	0.69	0.29809	0	0.30599	0.359166	0.298092	-0.017432
## 70	0.70	0.27470	0	0.27418	0.353291	0.274695	-0.018519
## 71	0.71	0.24968	0	0.25222	0.345110	0.249685	-0.019680
## 72	0.72	0.22289	0	0.28222	0.319955	0.222888	-0.020924
## 73	0.73	0.19411	0	0.27617	0.292384	0.205558	-0.027310
## 74	0.74	0.16311	0	0.26996	0.275377	0.207393	-0.028749
## 75	0.75	0.12963	0	0.24835	0.253058	0.193470	-0.030303
## 76	0.76	0.09337	0	0.23931	0.228880	0.191085	-0.031987
## 77	0.77	0.05395	0	0.21590	0.213238	0.242216	-0.033816
## 78	0.78	0.01095	0	0.18189	0.185477	0.191137	-0.035813
## 79	0.79	-0.03615	0	0.15520	0.140073	0.137037	-0.037999
## 80	0.80	-0.08796	0	0.12499	0.153385	0.135222	0.005051
## 81	0.81	-0.14522	0	0.08723	0.112516	0.060068	0.005051
## 82	0.82	-0.20884	0	0.04583	0.080047	0.008168	0.005051
## 83	0.83	-0.27995	0	0.04404	0.109761	-0.021500	0.005051
## 84	0.84	-0.35995	0	0.03971	0.063845	0.006594	0.005051
## 85	0.85	-0.45061	0	0.07195	0.092500	0.065285	0.005051
## 86	0.86	-0.55422	0	0.08482	0.086003	0.108750	0.005051
## 87	0.87	-0.67378	0	0.07549	0.064280	0.153323	0.005051
## 88	0.88	-0.81326	0	0.02418	-0.004204	0.159205	0.005051
## 89	0.89	-0.97810	0	-0.03420	-0.074473	0.132422	0.005051
## 90	0.90	-1.17591	0	-0.09098	-0.056582	0.106061	0.005051
## 91	0.91	-1.41768	0	-0.01565	-0.027184	0.120611	NA
## 92	0.92	-1.71989	0	-0.01695	-0.022529	0.144231	NA
## 93	0.93	-2.10845	0	-0.02506	-0.090834	0.093764	NA
## 94	0.94	-2.62652	0	-0.02027	-0.008936	0.016835	NA
## 95	0.95	-3.35183	0	-0.04467	-0.005393	NA	NA
## 96	0.96	-4.43979	0	-0.05556	-0.086287	NA	NA
## 97	0.97	-6.25305	0	-0.01331	-0.226750	NA	NA
## 98	0.98	-9.87957	0	-0.11111	-0.256410	NA	NA
## 99	0.99	-20.75914	0	-0.40909	-0.350168	NA	NA
##	mskcc.post.3						
## 1	0.780211						
## 2	0.777968						
## 3	0.775679						
## 4	0.773342						
## 5	0.770956						
## 6	0.768520						
## 7	0.766031						
## 8	0.763488						
## 9	0.760889						

## 10	0.758232
## 11	0.755515
## 12	0.752737
## 13	0.749895
## 14	0.746987
## 15	0.744010
## 16	0.740963
## 17	0.737842
## 18	0.734645
## 19	0.731369
## 20	0.728011
## 21	0.724568
## 22	0.721037
## 23	0.717414
## 24	0.713695
## 25	0.709878
## 26	0.705958
## 27	0.701930
## 28	0.697790
## 29	0.693533
## 30	0.689155
## 31	0.684650
## 32	0.680013
## 33	0.675237
## 34	0.670316
## 35	0.665244
## 36	0.660013
## 37	0.658248
## 38	0.652817
## 39	0.651133
## 40	0.649571
## 41	0.651851
## 42	0.655117
## 43	0.648430
## 44	0.627034
## 45	0.590163
## 46	0.575938
## 47	0.570415
## 48	0.561708
## 49	0.561741
## 50	0.550016
## 51	0.534803
## 52	0.519843
## 53	0.478884
## 54	0.454252
## 55	0.442167
## 56	0.413379
## 57	0.374308
## 58	0.343137
## 59	0.330506
## 60	0.280300
## 61	0.274222
## 62	0.228301
## 63	0.151937

```

## 64      0.158286
## 65      0.141877
## 66      0.121667
## 67      0.098262
## 68      0.074435
## 69      0.050033
## 70      0.007552
## 71      0.006941
## 72     -0.002202
## 73     -0.017770
## 74     -0.026171
## 75     -0.011111
## 76     -0.020202
## 77     -0.009076
## 78          NA
## 79          NA
## 80          NA
## 81          NA
## 82          NA
## 83          NA
## 84          NA
## 85          NA
## 86          NA
## 87          NA
## 88          NA
## 89          NA
## 90          NA
## 91          NA
## 92          NA
## 93          NA
## 94          NA
## 95          NA
## 96          NA
## 97          NA
## 98          NA
## 99          NA
##
## $interventions.avoided
##      threshold      gg.3      cph.3      rsf.3 mskcc.pre.3 mskcc.post.3
## 1      0.01  0.00000  0.00000  0.0000  0.00000  0.0000
## 2      0.02  0.00000  0.00000  0.0000  0.00000  0.0000
## 3      0.03  0.00000  0.00000  0.0000  0.00000  0.0000
## 4      0.04  0.00000  0.00000  0.0000  0.00000  0.0000
## 5      0.05  0.00000  0.00000  0.0000  0.00000  0.0000
## 6      0.06  0.00000  0.00000  0.0000  0.00000  0.0000
## 7      0.07  0.00000  0.00000  0.0000  0.00000  0.0000
## 8      0.08  0.00000  0.00000  0.0000  0.00000  0.0000
## 9      0.09  0.00000  0.00000  0.0000  0.00000  0.0000
## 10     0.10  0.00000  0.00000  0.0000  0.00000  0.0000
## 11     0.11  0.00000  0.00000  0.0000  0.00000  0.0000
## 12     0.12  0.00000  0.00000  0.0000  0.00000  0.0000
## 13     0.13  0.00000  0.00000  0.0000  0.00000  0.0000
## 14     0.14  0.00000  0.00000  0.0000  0.00000  0.0000
## 15     0.15  0.00000  0.00000  0.0000  0.00000  0.0000

```

## 16	0.16	0.00000	0.00000	0.0000	0.00000	0.0000
## 17	0.17	0.00000	0.00000	0.0000	0.00000	0.0000
## 18	0.18	0.00000	0.00000	0.0000	0.00000	0.0000
## 19	0.19	0.00000	0.00000	0.0000	0.00000	0.0000
## 20	0.20	0.00000	0.00000	0.0000	0.00000	0.0000
## 21	0.21	0.00000	0.00000	0.0000	0.00000	0.0000
## 22	0.22	0.00000	0.00000	0.0000	0.00000	0.0000
## 23	0.23	0.00000	0.00000	0.0000	0.00000	0.0000
## 24	0.24	0.00000	0.00000	0.0000	0.00000	0.0000
## 25	0.25	0.00000	0.00000	0.0000	0.00000	0.0000
## 26	0.26	0.00000	0.00000	0.0000	0.00000	0.0000
## 27	0.27	0.00000	0.00000	0.0000	0.00000	0.0000
## 28	0.28	0.00000	0.00000	0.0000	0.00000	0.0000
## 29	0.29	0.00000	0.00000	0.0000	0.00000	0.0000
## 30	0.30	0.00000	0.00000	0.0000	0.00000	0.0000
## 31	0.31	0.00000	0.00000	0.0000	0.00000	0.0000
## 32	0.32	0.00000	0.00000	0.0000	0.00000	0.0000
## 33	0.33	0.00000	0.00000	0.0000	0.00000	0.0000
## 34	0.34	0.00000	0.00000	0.0000	0.00000	0.0000
## 35	0.35	0.00000	0.00000	0.0000	0.00000	0.0000
## 36	0.36	0.00000	0.00000	0.0000	0.00000	0.0000
## 37	0.37	0.00000	0.00000	0.0000	0.00000	0.6183
## 38	0.38	0.00000	0.00000	0.0000	0.00000	0.6153
## 39	0.39	0.00000	0.00000	0.0000	0.00000	1.2264
## 40	0.40	0.00000	0.00000	0.0000	0.00000	1.8335
## 41	0.41	0.00000	0.00000	0.0000	0.00000	2.9716
## 42	0.42	0.00000	0.00000	0.0000	0.00000	4.1808
## 43	0.43	0.00000	0.00000	0.0000	0.00000	3.9993
## 44	0.44	0.00000	0.00000	0.0000	0.00000	1.9842
## 45	0.45	0.00000	0.00000	0.0000	0.00000	-1.7375
## 46	0.46	0.00000	0.00000	0.0000	0.00000	-2.4787
## 47	0.47	0.00000	0.00000	0.0000	0.00000	-2.1466
## 48	0.48	0.00000	0.00000	0.0000	0.00000	-2.1501
## 49	0.49	0.00000	0.00000	0.0000	0.00000	-1.2083
## 50	0.50	0.00000	0.00000	0.0000	0.00000	-1.4801
## 51	0.51	0.00000	0.00000	0.0000	-0.35408	-2.0304
## 52	0.52	0.00000	0.00000	0.0000	-0.10088	-2.4777
## 53	0.53	0.00000	0.00000	0.0000	-1.20618	-5.1572
## 54	0.54	0.00000	0.00000	0.0000	-0.48675	-6.1950
## 55	0.55	0.58124	0.00000	0.0000	0.22599	-6.0788
## 56	0.56	0.57988	0.00000	0.0000	0.34822	-7.2360
## 57	0.57	0.57856	0.00000	0.0000	-3.31476	-9.0274
## 58	0.58	0.57730	0.00000	0.0000	-11.12074	-10.0502
## 59	0.59	0.57607	0.00000	0.0000	-28.46915	-9.6442
## 60	0.60	0.57489	0.00000	0.0000	-30.73813	-11.7148
## 61	0.61	0.57374	0.00000	0.0000	-28.95090	-10.7315
## 62	0.62	0.57264	0.00000	0.0000	-26.89548	-12.2023
## 63	0.63	0.57156	-0.05426	0.0000	-24.90532	-15.2686
## 64	0.64	0.57052	-0.02928	0.0000	-22.97735	-13.3477
## 65	0.65	0.27824	0.56831	0.0000	-21.10870	-12.7310
## 66	0.66	0.28933	0.04444	0.0000	-19.29668	-12.2790
## 67	0.67	0.30008	0.09654	0.0000	-17.53874	-11.9376
## 68	0.68	0.23692	2.11662	0.0000	-15.83251	-11.5573
## 69	0.69	0.35482	2.74388	0.0000	-14.17574	-11.1447

## 70	0.70	-0.02191	3.36841	0.0000	-12.56630	-11.4490
## 71	0.71	0.10356	3.89763	0.0000	-11.00220	-9.9149
## 72	0.72	2.30740	3.77482	0.0000	-9.48155	-8.7535
## 73	0.73	3.03529	3.63493	0.4236	-8.18936	-7.8365
## 74	0.74	3.75409	3.94451	1.5559	-6.74099	-6.6504
## 75	0.75	3.95736	4.11414	2.1279	-5.33124	-4.6915
## 76	0.76	4.60876	4.27930	3.0858	-3.95860	-3.5865
## 77	0.77	4.83750	4.75793	5.6235	-2.62160	-1.8826
## 78	0.78	4.82157	4.92261	5.0823	-1.31889	NA
## 79	0.79	5.08658	4.68439	4.6037	-0.04916	NA
## 80	0.80	5.32357	6.03356	5.5795	2.32519	NA
## 81	0.81	5.45241	6.04562	4.8154	3.52482	NA
## 82	0.82	5.59026	6.34144	4.7636	4.69519	NA
## 83	0.83	6.63586	7.98203	5.2936	5.83735	NA
## 84	0.84	7.61259	8.07222	6.9817	6.95232	NA
## 85	0.85	9.22164	9.58428	9.1040	8.04106	NA
## 86	0.86	10.40304	10.42232	10.7926	9.10448	NA
## 87	0.87	11.19596	11.02848	12.3590	10.14345	NA
## 88	0.88	11.41969	11.03261	13.2609	11.15881	NA
## 89	0.89	11.66625	11.16847	13.7256	12.15135	NA
## 90	0.90	12.05486	12.43702	14.2442	13.12183	NA
## 91	0.91	13.86627	13.75218	15.2139	NA	NA
## 92	0.92	14.80820	14.75969	16.2098	NA	NA
## 93	0.93	15.68139	15.18635	16.5758	NA	NA
## 94	0.94	16.63565	16.70801	16.8725	NA	NA
## 95	0.95	17.40608	17.61282	NA	NA	NA
## 96	0.96	18.26763	18.13958	NA	NA	NA
## 97	0.97	19.29817	18.63803	NA	NA	NA
## 98	0.98	19.93563	19.63910	NA	NA	NA
## 99	0.99	20.55561	20.61513	NA	NA	NA

4.6 Brier score

```
calcIBS = function(surv, pred, pred_times, max_time)
{
  stopifnot(nrow(surv) == nrow(pred) && length(pred_times) == ncol(pred))

  n = nrow(surv)
  marg_survfit = survfit(surv ~ 1)
  marg_censfit = survfit(Surv(surv[,1], !surv[,2]) ~ 1)
  marg_surv_func = approxfun(marg_survfit$time, marg_survfit$surv, method = "constant", yleft = 1, yright = 0)
  marg_cens_func = approxfun(marg_censfit$time, marg_censfit$surv, method = "constant", yleft = 1, yright = 0)

  pred_funcs = apply(pred, 1, function(pat_preds) approxfun(pred_times, pat_preds, yleft = 1, yright = 0))

  indiv_patient_bsc = function(pat_i, tstars)
  {
    observed_time = surv[pat_i, 1]
    observed_event = surv[pat_i, 2]
    pred_func = pred_funcs[[pat_i]]
    category = 1*(observed_time <= tstars & observed_event) + 2*(observed_time > tstars) + 3*(observed_time >= max_time & !observed_event)
    bsc = rep(NA, length(tstars))
  }
}
```

```

        bsc[category == 1] = pred_func(tstars[category == 1])^2 / marg_cens_func(observed_time)
        bsc[category == 2] = (1 - pred_func(tstars[category == 2]))^2 / marg_cens_func(tstars[category == 2])
        bsc[category == 3] = 0
      bsc
    }

    bsc_func = function(tstars) { rowMeans(sapply(1:n, function(pat_i) indiv_patient_bsc(pat_i, tstars))) }

    weight_func = function(tstars) { (1 - marg_surv_func(tstars)) / (1 - marg_surv_func(max_time)) }

    # Be slack and do trapezoidal int. with a fine grid. It should be possible
    # to calculate the int. exactly but I cbfed.
    int_grid = seq(0, max_time, length.out = 1e3)
    bsc_vals = bsc_func(int_grid)
    weight_vals = weight_func(int_grid)
    int_vals = bsc_vals * weight_vals
    ibsc = (2*sum(int_vals) - int_vals[1] - int_vals[length(int_vals)]) * (diff(range(int_grid))) /

    return(list(bsc = bsc_vals, weights = weight_vals, eval_times = int_grid, ibsc = ibsc))
  }

calcBSsingle = function(surv, pred, pred_time)
{
  n = nrow(surv)
  obs_time = surv[,1]
  obs_event = surv[,2]
  marg_censfit = survfit(Surv(obs_time, !obs_event) ~ 1)
  marg_cens_func = approxfun(marg_censfit$time, marg_censfit$surv, method = "constant", yleft = 1, yright = 0)

  brier_val = rep(NA, n)
  cat = 1*I(obs_time <= pred_time & obs_event) + 2*I(obs_time > pred_time) + 3*I(obs_time <= pred_time & !obs_event)
  brier_val[cat == 1] = (pred[cat == 1])^2 / marg_cens_func(obs_time[cat == 1])
  brier_val[cat == 2] = (1-pred[cat == 2])^2 / marg_cens_func(pred_time)
  brier_val[cat == 3] = 0

  mean(brier_val)
}

```

```

mskcc_post.12mo.glasgow.brier = calcBSsingle(Surv(data.glasgow$Time, data.glasgow$DSD), mskcc_post.12mo.glasgow$surv, mskcc_post.12mo.glasgow$pred)
mskcc_post.24mo.glasgow.brier = calcBSsingle(Surv(data.glasgow$Time, data.glasgow$DSD), mskcc_post.24mo.glasgow$surv, mskcc_post.24mo.glasgow$pred)
mskcc_post.36mo.glasgow.brier = calcBSsingle(Surv(data.glasgow$Time, data.glasgow$DSD), mskcc_post.36mo.glasgow$surv, mskcc_post.36mo.glasgow$pred)
mskcc_pre.12mo.glasgow.brier = calcBSsingle(Surv(data.glasgow$Time, data.glasgow$DSD), mskcc_pre.12mo.glasgow$surv, mskcc_pre.12mo.glasgow$pred)
mskcc_pre.24mo.glasgow.brier = calcBSsingle(Surv(data.glasgow$Time, data.glasgow$DSD), mskcc_pre.24mo.glasgow$surv, mskcc_pre.24mo.glasgow$pred)
mskcc_pre.36mo.glasgow.brier = calcBSsingle(Surv(data.glasgow$Time, data.glasgow$DSD), mskcc_pre.36mo.glasgow$surv, mskcc_pre.36mo.glasgow$pred)
gg.path.glasgow.brier = calcIBS(Surv(data.glasgow$Time, data.glasgow$DSD), t(sapply(gg.path.glasgow, function(x) calcBSsingle(Surv(x$Time, x$DSD), x$surv, x$pred))))

km0.path.glasgow.brier = calcIBS(Surv(data.glasgow$Time, data.glasgow$DSD), matrix(fit.km0$surv, nrow = nrow(data.glasgow), byrow = TRUE))

temp.cph.pred = survfit(fit.cph, newdata = data.glasgow)
temp.cph.pred.expanded_strata = rep(names(temp.cph.pred$strata), temp.cph.pred$strata)
temp.cph.pred_funcs = sapply(rownames(data.glasgow), function(pat_id) {
  approxfun(temp.cph.pred$time[temp.cph.pred.expanded_strata == pat_id], temp.cph.pred$surv[temp.cph.pred.expanded_strata == pat_id])
})

```

```

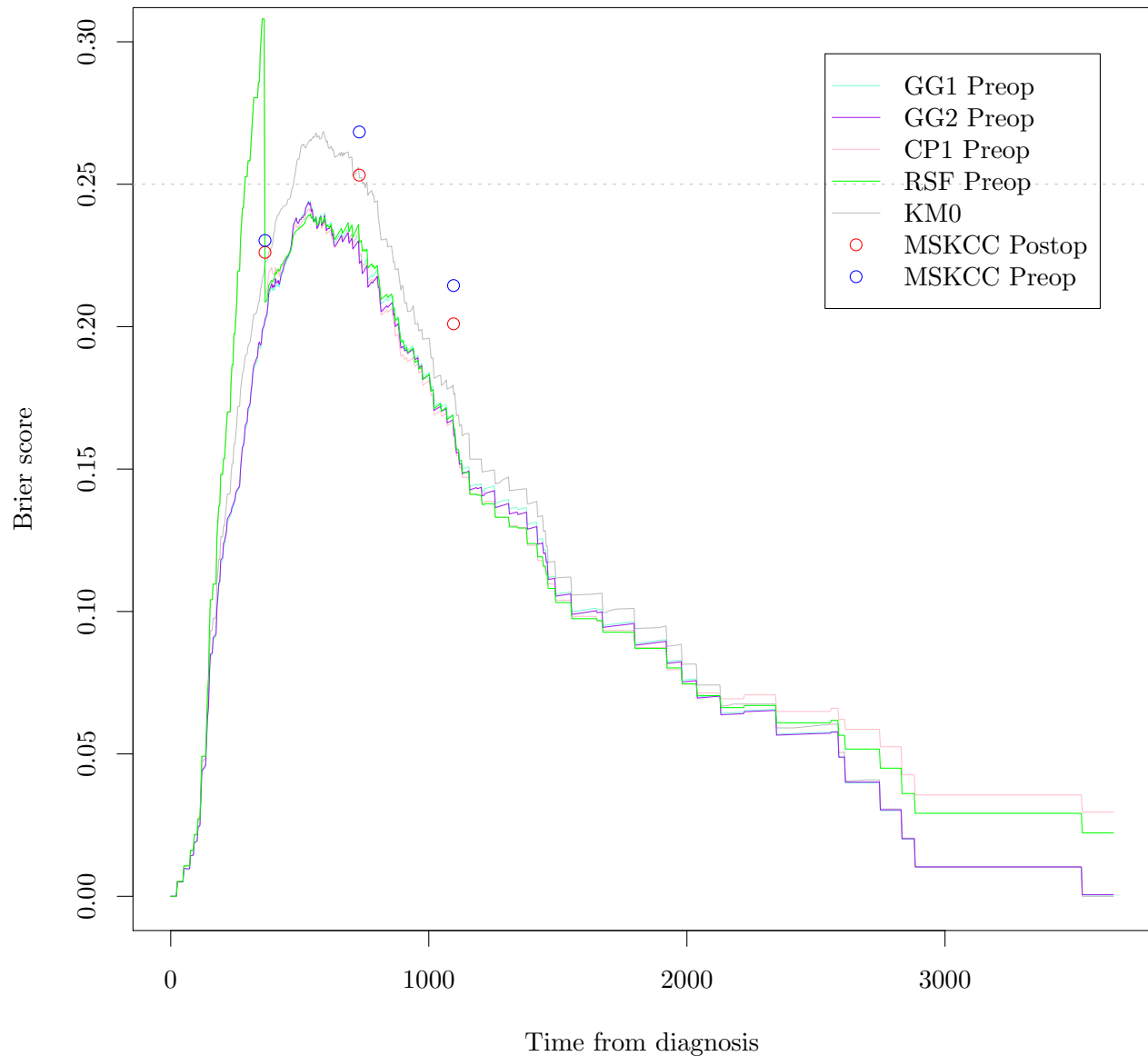
cph.path.glasgow.brier = calcIBS(Surv(data.glasgow$Time, data.glasgow$DSD),
  t(sapply(temp.cph.pred_funcs[rownames(data.glasgow)], function(f) f(c(12, 24, 36)/12*365.25))),

gg2.path.glasgow.brier = calcIBS(Surv(data.glasgow$Time, data.glasgow$DSD), t(sapply(gg2.path.glasgow, f

temp.rsfc.pred = predict(fit.rsfc, newdata = data.glasgow)
rsfc.path.glasgow.brier = calcIBS(Surv(data.glasgow$Time, data.glasgow$DSD), t(apply(temp.rsfc.pred$surviv

plot(gg.path.glasgow.brier$bsc ~ gg.path.glasgow.brier$eval_times, col = "aquamarine", type = "l", ylim
lines(km0.path.glasgow.brier$bsc ~ km0.path.glasgow.brier$eval_times, col = "grey")
lines(cph.path.glasgow.brier$bsc ~ cph.path.glasgow.brier$eval_times, col = "pink")
lines(gg2.path.glasgow.brier$bsc ~ gg2.path.glasgow.brier$eval_times, col = "purple")
lines(rsfc.path.glasgow.brier$bsc ~ rsfc.path.glasgow.brier$eval_times, col = "green")
points(c(12, 24, 36)/12*365.25, c(mskcc_post.12mo.glasgow.brier, mskcc_post.24mo.glasgow.brier, mskcc_pre
points(c(12, 24, 36)/12*365.25, c(mskcc_pre.12mo.glasgow.brier, mskcc_pre.24mo.glasgow.brier, mskcc_pre
abline(h = 0.25, col = "grey", lty = "dotted")
legend("topright",
  legend = c(      "GG1 Preop",      "GG2 Preop",      "CP1 Preop",      "RSF Preop",      "KM0",
  pch = c(         NA,                NA,                NA,                NA,                NA,
  col = c(         "aquamarine",      "purple",                "pink",                "green",
  lty = c(         "solid",                "solid",                "solid",                "solid",
  inset = 0.05)

```



```

probs_bs_boot_func = function(d, i) {
  bs.mskcc.postop.12 = calcBSsingle(Surv(d$Time[i], d$DSD[i]), mskcc_post.12mo.glasgow[i], 12/12*365.25)
  bs.mskcc.postop.24 = calcBSsingle(Surv(d$Time[i], d$DSD[i]), mskcc_post.24mo.glasgow[i], 24/12*365.25)
  bs.mskcc.postop.36 = calcBSsingle(Surv(d$Time[i], d$DSD[i]), mskcc_post.36mo.glasgow[i], 36/12*365.25)
  bs.mskcc.preop.12 = calcBSsingle(Surv(d$Time[i], d$DSD[i]), mskcc_pre.12mo.glasgow[i], 12/12*365.25)
  bs.mskcc.preop.24 = calcBSsingle(Surv(d$Time[i], d$DSD[i]), mskcc_pre.24mo.glasgow[i], 24/12*365.25)
  bs.mskcc.preop.36 = calcBSsingle(Surv(d$Time[i], d$DSD[i]), mskcc_pre.36mo.glasgow[i], 36/12*365.25)

  bs.gg.vals = t(sapply(gg.path.glasgow[i], function(path) approx(path[,1], path[,2], c(12, 24, 36))))
  rownames(bs.gg.vals) <- NULL
  bs.gg.12 = calcBSsingle(Surv(d$Time[i], d$DSD[i]), bs.gg.vals[,1], 12/12*365.25)
  bs.gg.24 = calcBSsingle(Surv(d$Time[i], d$DSD[i]), bs.gg.vals[,2], 24/12*365.25)
  bs.gg.36 = calcBSsingle(Surv(d$Time[i], d$DSD[i]), bs.gg.vals[,3], 36/12*365.25)

  cph.pred = survfit(fit.cph, newdata = d[i,])
  cph.pred.expanded_strata = rep(names(cph.pred$strata), cph.pred$strata)
  cph.pred_funcs = sapply(rownames(d)[i], function(pat_id) {

```



```

    approxfun(cph.pred$time[cph.pred$expanded_strata == pat_id], cph.pred$surv[cph.pred$expanded_strata == pat_id])
  })
  bs.cph.12 = calcBSsingle(Surv(d$time[i], d$DSD[i]), sapply(rownames(d)[i], function(pat_id) cph.pred$surv[cph.pred$expanded_strata == pat_id]))
  bs.cph.24 = calcBSsingle(Surv(d$time[i], d$DSD[i]), sapply(rownames(d)[i], function(pat_id) cph.pred$surv[cph.pred$expanded_strata == pat_id]))
  bs.cph.36 = calcBSsingle(Surv(d$time[i], d$DSD[i]), sapply(rownames(d)[i], function(pat_id) cph.pred$surv[cph.pred$expanded_strata == pat_id]))

  bs.km0.vals = approx(fit.km0$time, fit.km0$surv, c(12, 24, 36)/12*365.25)$y
  bs.km0.12 = calcBSsingle(Surv(d$time[i], d$DSD[i]), rep(bs.km0.vals[1], nrow(d[i,])), 12/12*365.25)
  bs.km0.24 = calcBSsingle(Surv(d$time[i], d$DSD[i]), rep(bs.km0.vals[2], nrow(d[i,])), 24/12*365.25)
  bs.km0.36 = calcBSsingle(Surv(d$time[i], d$DSD[i]), rep(bs.km0.vals[3], nrow(d[i,])), 36/12*365.25)

  result = c(
    bs.cph.12 - bs.km0.12, bs.gg.12 - bs.km0.12, bs.msccc.preop.12 - bs.km0.12, bs.msccc.postop.12 - bs.km0.12,
    bs.cph.12 - bs.msccc.preop.12, bs.gg.12 - bs.msccc.preop.12, bs.msccc.postop.12 - bs.km0.12, bs.msccc.postop.12 - bs.km0.12,
    bs.cph.12 - bs.msccc.postop.12, bs.gg.12 - bs.msccc.postop.12, bs.msccc.postop.12 - bs.km0.12, bs.msccc.postop.12 - bs.km0.12,
    bs.cph.12 - bs.gg.12, bs.msccc.preop.12 - bs.km0.12, bs.msccc.postop.12 - bs.km0.12, bs.msccc.postop.12 - bs.km0.12,
    bs.cph.24 - bs.km0.24, bs.gg.24 - bs.km0.24, bs.msccc.preop.24 - bs.km0.24, bs.msccc.postop.24 - bs.km0.24,
    bs.cph.24 - bs.msccc.preop.24, bs.gg.24 - bs.msccc.preop.24, bs.msccc.postop.24 - bs.km0.24, bs.msccc.postop.24 - bs.km0.24,
    bs.cph.24 - bs.msccc.postop.24, bs.gg.24 - bs.msccc.postop.24, bs.msccc.postop.24 - bs.km0.24, bs.msccc.postop.24 - bs.km0.24,
    bs.cph.24 - bs.gg.24, bs.msccc.preop.24 - bs.km0.24, bs.msccc.postop.24 - bs.km0.24, bs.msccc.postop.24 - bs.km0.24,
    bs.cph.36 - bs.km0.36, bs.gg.36 - bs.km0.36, bs.msccc.preop.36 - bs.km0.36, bs.msccc.postop.36 - bs.km0.36,
    bs.cph.36 - bs.msccc.preop.36, bs.gg.36 - bs.msccc.preop.36, bs.msccc.postop.36 - bs.km0.36, bs.msccc.postop.36 - bs.km0.36,
    bs.cph.36 - bs.msccc.postop.36, bs.gg.36 - bs.msccc.postop.36, bs.msccc.postop.36 - bs.km0.36, bs.msccc.postop.36 - bs.km0.36,
    bs.cph.36 - bs.gg.36)
  names(result) <- NULL
  result
}

set.seed(20150113)
deltaBrier.boot.glasgow = boot(data.glasgow, probs_bs_boot_func, R = 500)
deltaBrier.boot.glasgow.cis = t(sapply(1:ncol(deltaBrier.boot.glasgow$t), function(i) boot.ci(deltaBrier.boot.glasgow, i, R = 500)))
colnames(deltaBrier.boot.glasgow.cis) = c("level", "lowindex", "highindex", "lci", "uci")
rownames(deltaBrier.boot.glasgow.cis) = c(
  "12:cph-km0", "12:gg-km0", "12:post-km0", "12:pre-km0", "12:cph-pre", "12:gg-pre", "12:post-pre", "12:pre-pre",
  "24:cph-km0", "24:gg-km0", "24:post-km0", "24:pre-km0", "24:cph-pre", "24:gg-pre", "24:post-pre", "24:pre-pre",
  "36:cph-km0", "36:gg-km0", "36:post-km0", "36:pre-km0", "36:cph-pre", "36:gg-pre", "36:post-pre", "36:pre-pre")
deltaBrier.boot.glasgow

##
## ORDINARY NONPARAMETRIC BOOTSTRAP
##
##
## Call:
## boot(data = data.glasgow, statistic = probs_bs_boot_func, R = 500)
##
##
## Bootstrap Statistics :
##      original      bias    std. error
## t1*  -0.0107346 -1.403e-03   0.012699
## t2*  -0.0207374 -1.474e-03   0.012316
## t3*   0.0037324 -1.033e-03   0.014366
## t4*   0.0078972 -6.393e-04   0.014648
## t5*  -0.0186318 -7.634e-04   0.022123
## t6*  -0.0286346 -8.347e-04   0.021348

```

```
## t7* -0.0041648 -3.935e-04 0.003150
## t8* -0.0144669 -3.699e-04 0.021773
## t9* -0.0244698 -4.413e-04 0.021043
## t10* 0.0100028 7.136e-05 0.002871
## t11* -0.0269945 -3.682e-04 0.010481
## t12* -0.0276310 -5.277e-04 0.011371
## t13* 0.0012760 -2.046e-03 0.020184
## t14* 0.0164211 -1.435e-03 0.020014
## t15* -0.0434155 1.067e-03 0.021542
## t16* -0.0440521 9.069e-04 0.021258
## t17* -0.0151451 -6.114e-04 0.005561
## t18* -0.0282704 1.678e-03 0.021498
## t19* -0.0289069 1.518e-03 0.021349
## t20* 0.0006365 1.596e-04 0.003258
## t21* -0.0148527 -5.323e-04 0.006927
## t22* -0.0125841 -4.967e-04 0.006582
## t23* 0.0250004 -2.048e-03 0.018127
## t24* 0.0384405 -1.355e-03 0.017079
## t25* -0.0532932 8.226e-04 0.016095
## t26* -0.0510246 8.582e-04 0.016575
## t27* -0.0134401 -6.928e-04 0.005662
## t28* -0.0398531 1.515e-03 0.016962
## t29* -0.0375845 1.551e-03 0.017465
## t30* -0.0022686 -3.562e-05 0.002097
```

deltaBrier.boot.glasgow.cis

```
## level lowindex highindex lci uci
## 12:cph-km0 0.95 22.47 494.6 -0.033541 0.0176629
## 12:gg-km0 0.95 27.48 496.0 -0.041289 0.0068133
## 12:post-km0 0.95 21.35 494.2 -0.022559 0.0366974
## 12:pre-km0 0.95 19.02 493.1 -0.018278 0.0418052
## 12:cph-pre 0.95 12.40 488.4 -0.067131 0.0237186
## 12:gg-pre 0.95 12.23 488.2 -0.075689 0.0107875
## 12:post-pre 0.95 16.63 491.5 -0.010614 0.0016693
## 12:cph-post 0.95 12.64 488.6 -0.062283 0.0271091
## 12:gg-post 0.95 13.72 489.6 -0.068918 0.0160026
## 12:cph-gg 0.95 9.64 484.9 0.003998 0.0156107
## 24:cph-km0 0.95 17.23 492.2 -0.047270 -0.0023518
## 24:gg-km0 0.95 16.03 491.4 -0.050938 -0.0046682
## 24:post-km0 0.95 19.91 493.3 -0.038033 0.0456494
## 24:pre-km0 0.95 16.14 491.3 -0.022332 0.0588605
## 24:cph-pre 0.95 7.52 480.5 -0.090353 -0.0054964
## 24:gg-pre 0.95 8.05 481.7 -0.088423 -0.0040642
## 24:post-pre 0.95 27.60 496.0 -0.024216 -0.0011646
## 24:cph-post 0.95 9.24 484.1 -0.072690 0.0136263
## 24:gg-post 0.95 9.18 484.0 -0.070728 0.0118507
## 24:cph-gg 0.95 13.51 489.4 -0.005582 0.0073935
## 36:cph-km0 0.95 19.98 493.2 -0.027265 -0.0001374
## 36:gg-km0 0.95 17.50 492.0 -0.024773 0.0008830
## 36:post-km0 0.95 18.52 492.5 -0.011102 0.0612558
## 36:pre-km0 0.95 12.00 488.0 0.004356 0.0706008
## 36:cph-pre 0.95 14.40 490.3 -0.083752 -0.0202140
## 36:gg-pre 0.95 13.03 489.0 -0.082932 -0.0168767
```

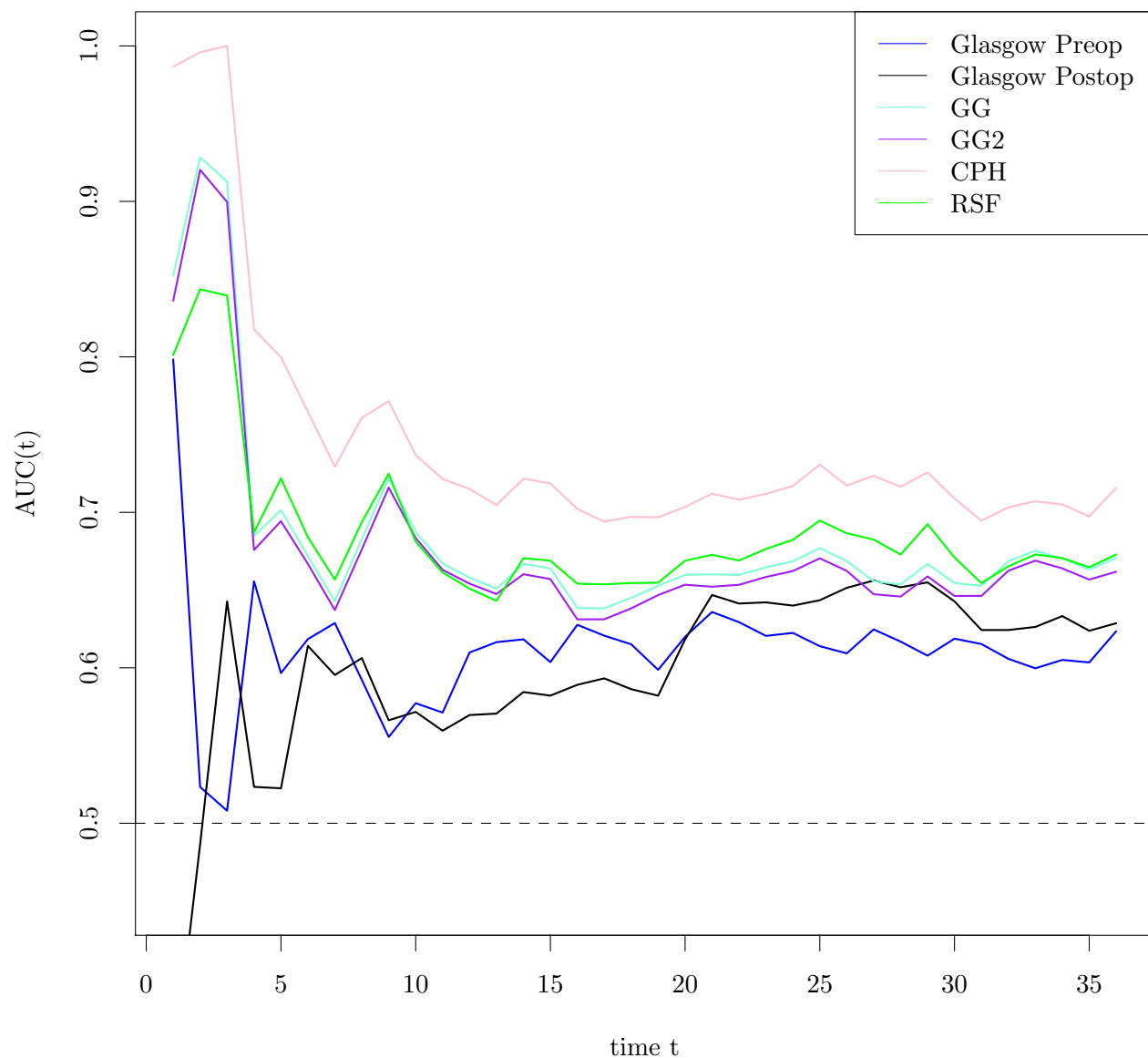
```
## 36:post-pre 0.95 22.31 494.5 -0.024201 -0.0017397
## 36:cph-post 0.95 10.84 486.4 -0.072570 -0.0042446
## 36:gg-post 0.95 11.01 486.6 -0.070536 -0.0020764
## 36:cph-gg 0.95 13.56 489.5 -0.006236 0.0020161
```

```
temp.time = gsub(".*", "", rownames(deltaBrier.boot.glasgow.cis))
temp.methodpos = gsub(".*:", "", gsub(".*", "", rownames(deltaBrier.boot.glasgow.cis)))
temp.methodneg = gsub(".*-", "", rownames(deltaBrier.boot.glasgow.cis))
temp.methods = sort(unique(c(temp.methodpos, temp.methodneg)))
tapply(1:length(temp.time), temp.time, function(is) {
  res = matrix(0, nrow = length(temp.methods), ncol = length(temp.methods))
  rownames(res) = temp.methods
  colnames(res) = temp.methods
  # Make res signed. 0 => NS. +1 => row is better than col (BS_row - BS_col < 0). -1 => row is
  res[cbind(temp.methodpos[is], temp.methodneg[is])] = (sign(deltaBrier.boot.glasgow.cis[is, "uci
  res[cbind(temp.methodneg[is], temp.methodpos[is])] = (sign(deltaBrier.boot.glasgow.cis[is, "uci
  res
})

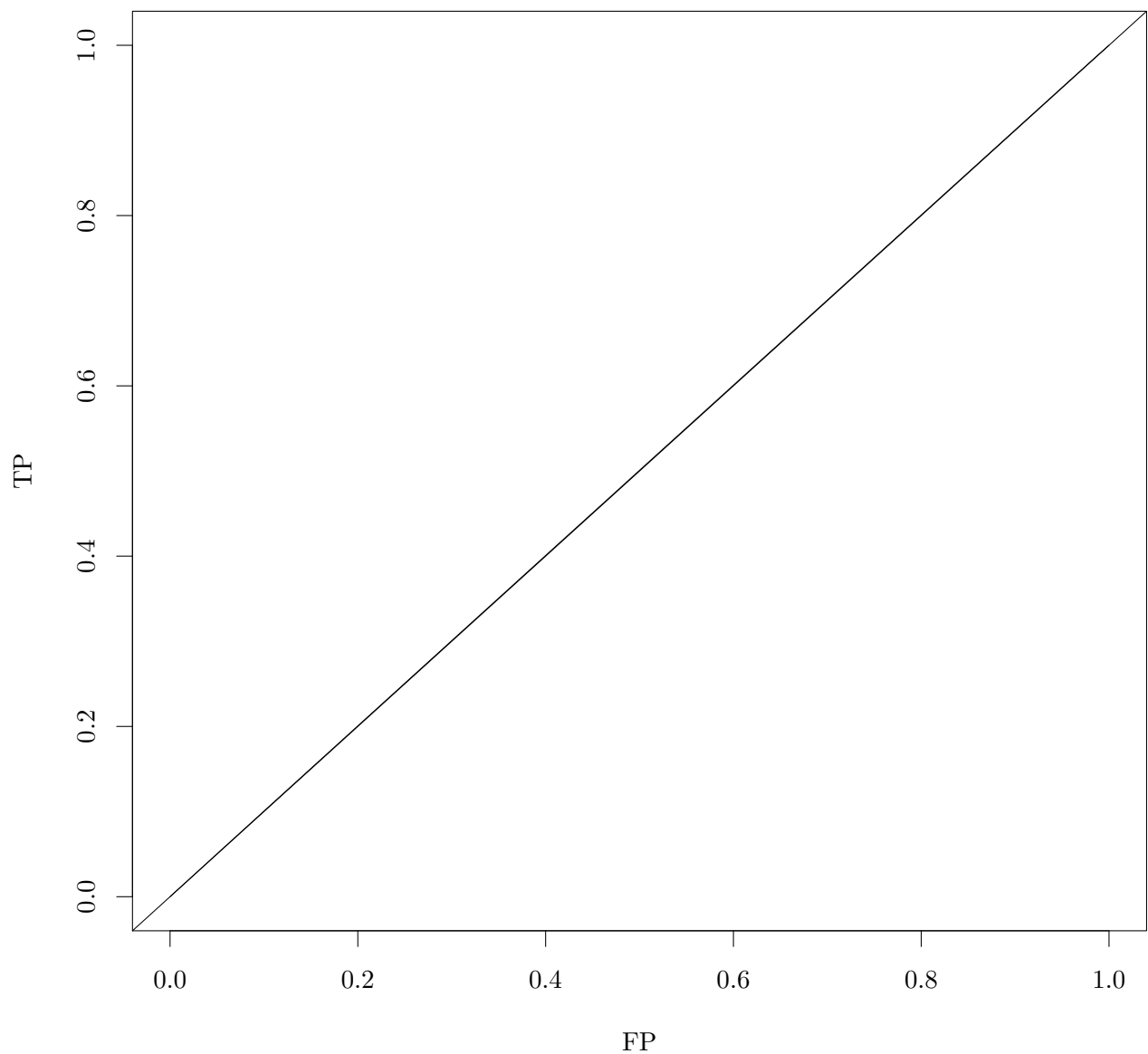
## $`12`
##      cph gg km0 post pre
## cph    0 -1  0   0   0
## gg     1  0  0   0   0
## km0    0  0  0   0   0
## post   0  0  0   0   0
## pre    0  0  0   0   0
##
## $`24`
##      cph gg km0 post pre
## cph    0  0  1   0   1
## gg     0  0  1   0   1
## km0   -1 -1  0   0   0
## post   0  0  0   0   1
## pre   -1 -1  0  -1   0
##
## $`36`
##      cph gg km0 post pre
## cph    0  0  1   1   1
## gg     0  0  0   1   1
## km0   -1  0  0   0   1
## post  -1 -1  0   0   1
## pre   -1 -1 -1  -1   0
```

```
mskcc_pre.cdroc.glasgow = timeROC(data.glasgow$Time/365.25*12, data.glasgow$DSD, mskcc_pre.linpred.glasgow)
mskcc_post.cdroc.glasgow = timeROC(data.glasgow$Time/365.25*12, data.glasgow$DSD, mskcc_post.linpred.glasgow)
gg.cdroc.glasgow = timeROC(data.glasgow$Time/365.25*12, data.glasgow$DSD, gg.linpred.glasgow, cause = 1)
gg2.cdroc.glasgow = timeROC(data.glasgow$Time/365.25*12, data.glasgow$DSD, gg2.linpred.glasgow, cause = 1)
cph.cdroc.glasgow = timeROC(data.glasgow$Time/365.25*12, data.glasgow$DSD, cph.linpred.glasgow, cause = 1)
rsf.cdroc.glasgow = timeROC(data.glasgow$Time/365.25*12, data.glasgow$DSD, rsf.linpred.glasgow, cause = 1)
plotAUCcurve(mskcc_pre.cdroc.glasgow, conf.int = FALSE, add = FALSE, col = "blue")
plotAUCcurve(mskcc_post.cdroc.glasgow, conf.int = FALSE, add = TRUE, col = "black")
plotAUCcurve(gg.cdroc.glasgow, conf.int = FALSE, add = TRUE, col = "aquamarine")
```

```
plotAUCcurve(gg2.cdroc.glasgow, conf.int = FALSE, add = TRUE, col = "purple")
plotAUCcurve(cph.cdroc.glasgow, conf.int = FALSE, add = TRUE, col = "pink")
plotAUCcurve(rsf.cdroc.glasgow, conf.int = FALSE, add = TRUE, col = "green")
legend("topright", legend = c("Glasgow Preop", "Glasgow Postop", "GG", "GG2", "CPH", "RSF"), col = c("blue", "black", "cyan", "purple", "pink", "green"))
```



```
risksetROC(data.glasgow$Time/365.25*12, status = data.glasgow$DSD, marker = mskcc_pre.linpred.glasgow, p
```



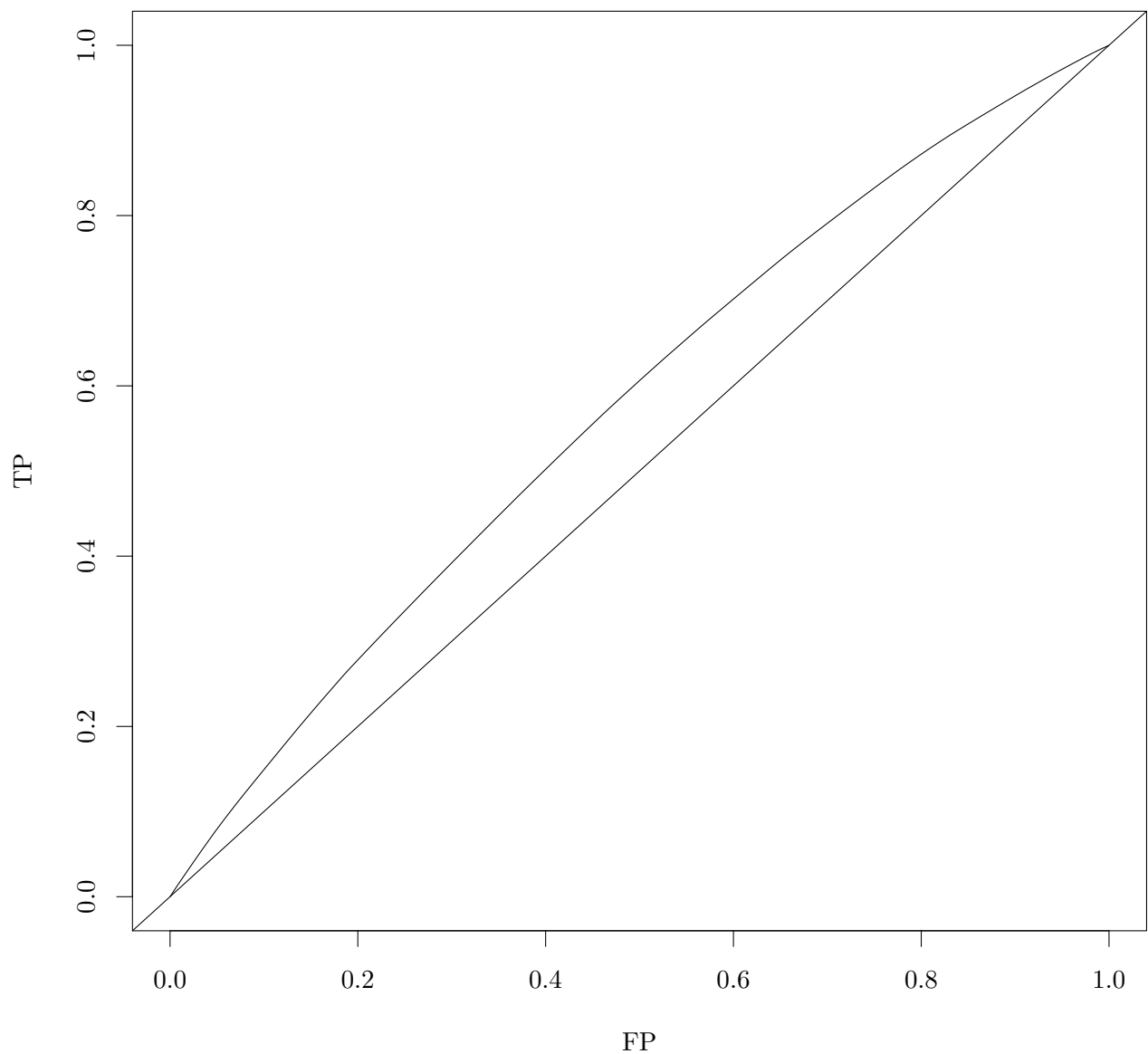
```
## $marker
## [1] -0.09676 -0.08538 -0.07023 -0.07019 -0.06997 -0.06977 -0.06961
## [8] -0.06958 -0.06955 -0.06950 -0.06947 -0.06928 -0.06917 -0.06916
## [15] -0.06910 -0.06904 -0.06896 -0.06895 -0.06894 -0.06888 -0.06884
## [22] -0.06884 -0.06881 -0.06876 -0.06867 -0.06867 -0.06865 -0.06864
## [29] -0.06860 -0.06860 -0.06859 -0.06859 -0.06856 -0.06856 -0.06855
## [36] -0.06854 -0.06852 -0.06851 -0.06851 -0.06850 -0.06848 -0.06844
## [43] -0.06839 -0.06831 -0.06831 -0.06830 -0.06826 -0.06826 -0.06824
## [50] -0.06823 -0.06823 -0.06823 -0.06823 -0.06823 -0.06822 -0.06821
## [57] -0.06819 -0.06817 -0.06814 -0.06812 -0.06807 -0.06805 -0.06799
## [64] -0.06797 -0.06797 -0.06797 -0.06790 -0.06787 -0.06787 -0.06778
## [71] -0.06775 -0.06772 -0.06755 -0.06752 -0.06752 -0.06750 -0.06748
## [78] -0.06748 -0.06746 -0.06744 -0.06743 -0.06743 -0.06731 -0.06725
## [85] -0.06723 -0.06723 -0.06721 -0.06715 -0.06713 -0.06710 -0.06710
## [92] -0.06709 -0.06704 -0.06704 -0.06703 -0.06703 -0.06703 -0.06703
## [99] -0.06695 -0.06689 -0.06688 -0.06688 -0.06687 -0.06687 -0.06685
## [106] -0.06680 -0.06675 -0.06670 -0.06669 -0.06662 -0.06658 -0.06512
```

```

## [113] -0.06443 -0.06388 -0.06340 -0.06317 -0.06315 -0.06312 -0.06263
## [120] -0.06246 -0.06235 -0.06222 -0.06208 -0.06185
##
## $TP
## [1] 1.000000 0.992165 0.984240 0.976194 0.968148 0.960100 0.952051
## [8] 0.944000 0.935949 0.927898 0.919846 0.911794 0.903741 0.895686
## [15] 0.887632 0.879577 0.871522 0.863466 0.855409 0.847353 0.839297
## [22] 0.831240 0.823183 0.815125 0.807068 0.799009 0.790951 0.782893
## [29] 0.774834 0.766775 0.758716 0.750657 0.742598 0.734539 0.726480
## [36] 0.718420 0.710361 0.702301 0.694242 0.686182 0.678122 0.670062
## [43] 0.662002 0.653942 0.645880 0.637819 0.629758 0.621696 0.613634
## [50] 0.605573 0.597511 0.589449 0.581387 0.573325 0.565263 0.557201
## [57] 0.549139 0.541077 0.533014 0.524952 0.516889 0.508826 0.500762
## [64] 0.492698 0.484635 0.476571 0.468507 0.460442 0.452377 0.444312
## [71] 0.436247 0.428181 0.420115 0.412048 0.403980 0.395912 0.387845
## [78] 0.379777 0.371709 0.363641 0.355572 0.347504 0.339436 0.331366
## [85] 0.323296 0.315226 0.307156 0.299086 0.291016 0.282945 0.274874
## [92] 0.266803 0.258732 0.250660 0.242589 0.234517 0.226446 0.218374
## [99] 0.210303 0.202230 0.194158 0.186085 0.178012 0.169939 0.161866
## [106] 0.153793 0.145720 0.137646 0.129572 0.121498 0.113423 0.105347
## [113] 0.097260 0.089168 0.081071 0.072970 0.064867 0.056764 0.048661
## [120] 0.040554 0.032445 0.024336 0.016225 0.008114 0.000000 0.000000
##
## $FP
## [1] 1.000000 0.991935 0.983871 0.975806 0.967742 0.959677 0.951613
## [8] 0.943548 0.935484 0.927419 0.919355 0.911290 0.903226 0.895161
## [15] 0.887097 0.879032 0.870968 0.862903 0.854839 0.846774 0.838710
## [22] 0.830645 0.822581 0.814516 0.806452 0.798387 0.790323 0.782258
## [29] 0.774194 0.766129 0.758065 0.750000 0.741935 0.733871 0.725806
## [36] 0.717742 0.709677 0.701613 0.693548 0.685484 0.677419 0.669355
## [43] 0.661290 0.653226 0.645161 0.637097 0.629032 0.620968 0.612903
## [50] 0.604839 0.596774 0.588710 0.580645 0.572581 0.564516 0.556452
## [57] 0.548387 0.540323 0.532258 0.524194 0.516129 0.508065 0.500000
## [64] 0.491935 0.483871 0.475806 0.467742 0.459677 0.451613 0.443548
## [71] 0.435484 0.427419 0.419355 0.411290 0.403226 0.395161 0.387097
## [78] 0.379032 0.370968 0.362903 0.354839 0.346774 0.338710 0.330645
## [85] 0.322581 0.314516 0.306452 0.298387 0.290323 0.282258 0.274194
## [92] 0.266129 0.258065 0.250000 0.241935 0.233871 0.225806 0.217742
## [99] 0.209677 0.201613 0.193548 0.185484 0.177419 0.169355 0.161290
## [106] 0.153226 0.145161 0.137097 0.129032 0.120968 0.112903 0.104839
## [113] 0.096774 0.088710 0.080645 0.072581 0.064516 0.056452 0.048387
## [120] 0.040323 0.032258 0.024194 0.016129 0.008065 0.000000 0.000000
##
## $AUC
## [1] 0.5006

risksetROC(data.glasgow$Time/365.25*12, status = data.glasgow$DSD, marker = mskcc_post.linpred.glasgow,

```



```
## $marker
## [1] 1.734 1.808 1.847 1.877 1.890 1.899 1.901 1.933 1.945 1.953 1.955
## [12] 1.980 1.984 1.990 2.001 2.009 2.009 2.012 2.016 2.032 2.033 2.086
## [23] 2.099 2.113 2.136 2.152 2.165 2.182 2.208 2.210 2.224 2.225 2.227
## [34] 2.229 2.233 2.240 2.245 2.248 2.252 2.259 2.261 2.286 2.295 2.320
## [45] 2.324 2.331 2.335 2.337 2.341 2.341 2.342 2.347 2.348 2.355 2.379
## [56] 2.379 2.382 2.384 2.388 2.403 2.404 2.415 2.425 2.426 2.427 2.437
## [67] 2.451 2.464 2.471 2.474 2.477 2.481 2.485 2.491 2.493 2.495 2.496
## [78] 2.499 2.515 2.515 2.515 2.521 2.524 2.524 2.527 2.527 2.529 2.531
## [89] 2.533 2.538 2.541 2.545 2.548 2.548 2.555 2.558 2.564 2.567 2.572
## [100] 2.572 2.604 2.650 2.656 2.656 2.669 2.679 2.685 2.710 2.711 2.714
## [111] 2.717 2.718 2.721 2.726 2.742 2.766 2.779 2.806 2.850 2.860 2.883
## [122] 2.884 2.895 2.938
##
## $TP
## [1] 1.00000 0.99594 0.99156 0.98701 0.98232 0.97757 0.97278 0.96798
## [9] 0.96302 0.95801 0.95295 0.94788 0.94269 0.93747 0.93222 0.92691
```

```
## [17] 0.92156 0.91621 0.91085 0.90546 0.89999 0.89451 0.88873 0.88288
## [25] 0.87695 0.87087 0.86471 0.85845 0.85209 0.84557 0.83903 0.83240
## [33] 0.82576 0.81911 0.81244 0.80575 0.79901 0.79224 0.78544 0.77862
## [41] 0.77175 0.76487 0.75782 0.75070 0.74340 0.73607 0.72869 0.72127
## [49] 0.71385 0.70640 0.69894 0.69148 0.68398 0.67648 0.66892 0.66118
## [57] 0.65343 0.64566 0.63788 0.63007 0.62214 0.61419 0.60616 0.59806
## [65] 0.58994 0.58181 0.57361 0.56529 0.55686 0.54837 0.53986 0.53132
## [73] 0.52275 0.51413 0.50547 0.49679 0.48810 0.47939 0.47066 0.46179
## [81] 0.45292 0.44405 0.43513 0.42618 0.41723 0.40825 0.39927 0.39027
## [89] 0.38126 0.37223 0.36315 0.35404 0.34490 0.33573 0.32657 0.31734
## [97] 0.30808 0.29875 0.28940 0.28001 0.27062 0.26092 0.25077 0.24056
## [105] 0.23035 0.22000 0.20955 0.19903 0.18825 0.17745 0.16663 0.15577
## [113] 0.14490 0.13400 0.12305 0.11191 0.10051 0.08895 0.07709 0.06469
## [121] 0.05217 0.03935 0.02651 0.01354 0.00000 0.00000
```

```
##
```

```
## $FP
```

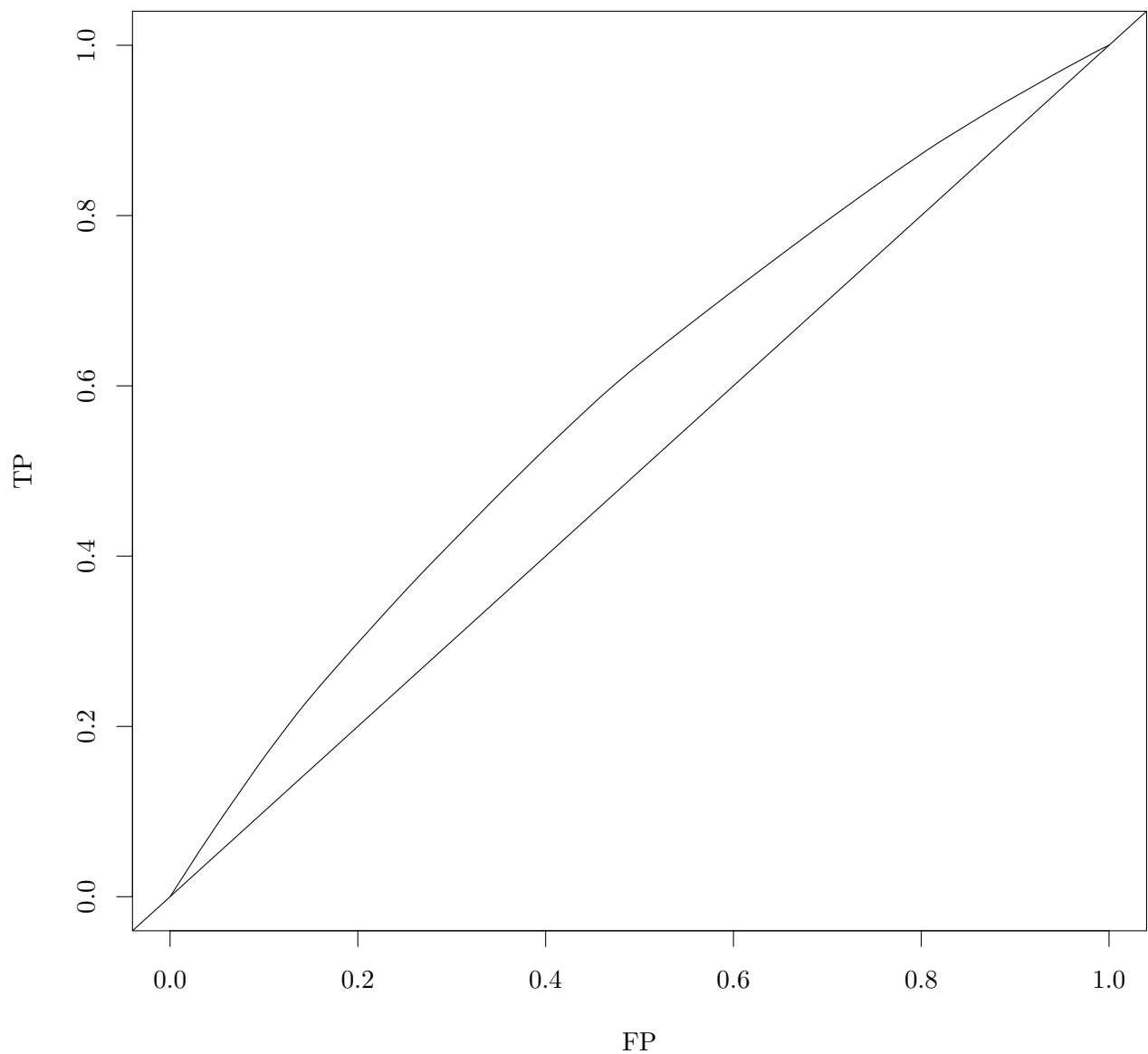
```
## [1] 1.000000 0.991935 0.983871 0.975806 0.967742 0.959677 0.951613
## [8] 0.943548 0.935484 0.927419 0.919355 0.911290 0.903226 0.895161
## [15] 0.887097 0.879032 0.870968 0.862903 0.854839 0.846774 0.838710
## [22] 0.830645 0.822581 0.814516 0.806452 0.798387 0.790323 0.782258
## [29] 0.774194 0.766129 0.758065 0.750000 0.741935 0.733871 0.725806
## [36] 0.717742 0.709677 0.701613 0.693548 0.685484 0.677419 0.669355
## [43] 0.661290 0.653226 0.645161 0.637097 0.629032 0.620968 0.612903
## [50] 0.604839 0.596774 0.588710 0.580645 0.572581 0.564516 0.556452
## [57] 0.548387 0.540323 0.532258 0.524194 0.516129 0.508065 0.500000
## [64] 0.491935 0.483871 0.475806 0.467742 0.459677 0.451613 0.443548
## [71] 0.435484 0.427419 0.419355 0.411290 0.403226 0.395161 0.387097
## [78] 0.379032 0.370968 0.362903 0.354839 0.346774 0.338710 0.330645
## [85] 0.322581 0.314516 0.306452 0.298387 0.290323 0.282258 0.274194
## [92] 0.266129 0.258065 0.250000 0.241935 0.233871 0.225806 0.217742
## [99] 0.209677 0.201613 0.193548 0.185484 0.177419 0.169355 0.161290
## [106] 0.153226 0.145161 0.137097 0.129032 0.120968 0.112903 0.104839
## [113] 0.096774 0.088710 0.080645 0.072581 0.064516 0.056452 0.048387
## [120] 0.040323 0.032258 0.024194 0.016129 0.008065 0.000000 0.000000
```

```
##
```

```
## $AUC
```

```
## [1] 0.5743
```

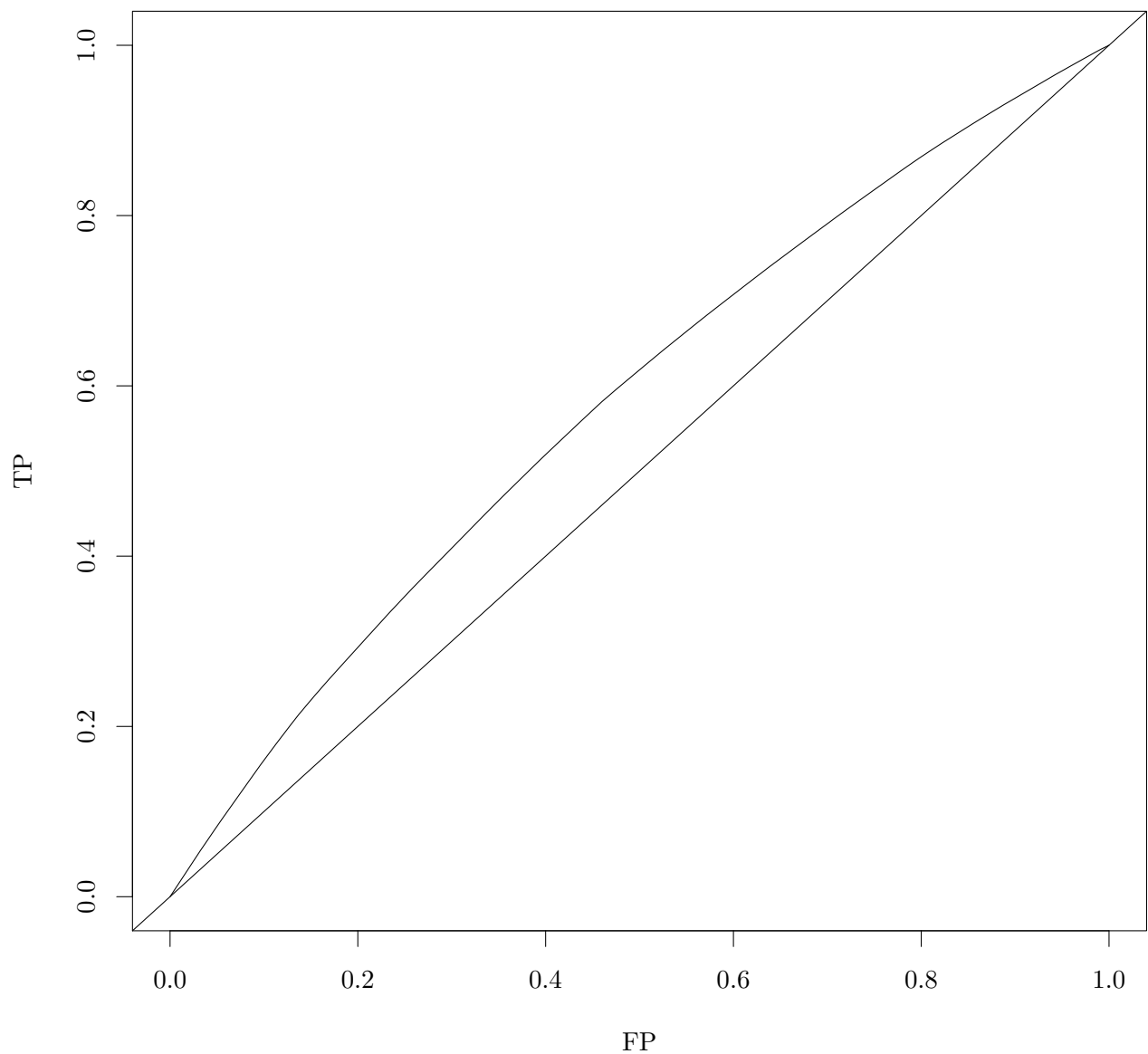
```
risksetROC(data.glasgow$Time/365.25*12, status = data.glasgow$DSD, marker = gg.linpred.glasgow, predict.
```

```
## $marker
## [1] -0.50102 -0.38477 -0.35377 -0.35377 -0.35377 -0.34602 -0.34602
## [8] -0.30727 -0.30727 -0.30727 -0.30727 -0.30727 -0.30727 -0.30727
## [15] -0.26852 -0.26852 -0.25302 -0.22977 -0.22977 -0.22977 -0.22977
## [22] -0.22091 -0.19102 -0.14341 -0.14341 -0.11625 -0.11625 -0.11351
## [29] -0.10466 -0.10075 -0.08916 -0.07750 -0.07750 -0.06591 -0.06591
## [36] -0.06591 -0.06591 -0.05816 -0.03875 -0.03875 -0.03875 -0.03875
## [43] -0.03100 -0.02716 -0.02716 -0.02716 -0.02716 -0.02716 -0.01941
## [50] -0.01550 -0.01166 0.00000 0.00000 0.00000 0.00000 0.00775
## [57] 0.01159 0.01159 0.01159 0.03875 0.03875 0.03875 0.03875
## [64] 0.08910 0.08910 0.12785 0.12785 0.17050 0.18711 0.18711
## [71] 0.19486 0.20261 0.20261 0.20261 0.23361 0.23659 0.24136
## [78] 0.24136 0.24136 0.24136 0.26461 0.26648 0.28011 0.28011
## [85] 0.28011 0.28011 0.28011 0.28011 0.28011 0.29084 0.31409
## [92] 0.31409 0.31886 0.34125 0.35284 0.35284 0.35761 0.35761
## [99] 0.35761 0.36450 0.39159 0.39159 0.39159 0.39159 0.43034
## [106] 0.43512 0.46909 0.51262 0.53500 0.54386 0.54386 0.57486
```

```
## [113] 0.61361 0.62136 0.62136 0.62136 0.62136 0.64461 0.66011
## [120] 0.66011 0.69886 0.69886 0.69886 0.69886
##
## $TP
## [1] 1.00000 0.99584 0.99117 0.98636 0.98154 0.97672 0.97187 0.96702
## [9] 0.96197 0.95692 0.95188 0.94683 0.94179 0.93674 0.93170 0.92645
## [17] 0.92120 0.91588 0.91043 0.90497 0.89952 0.89407 0.88857 0.88290
## [25] 0.87696 0.87101 0.86490 0.85880 0.85267 0.84649 0.84029 0.83401
## [33] 0.82766 0.82131 0.81489 0.80847 0.80204 0.79562 0.78915 0.78255
## [41] 0.77595 0.76935 0.76275 0.75610 0.74942 0.74274 0.73607 0.72939
## [49] 0.72271 0.71598 0.70923 0.70245 0.69559 0.68872 0.68186 0.67500
## [57] 0.66809 0.66115 0.65421 0.64727 0.64013 0.63300 0.62587 0.61874
## [65] 0.61124 0.60374 0.59594 0.58815 0.58001 0.57174 0.56346 0.55513
## [73] 0.54673 0.53832 0.52992 0.52126 0.51256 0.50383 0.49510 0.48636
## [81] 0.47763 0.46869 0.45973 0.45066 0.44158 0.43250 0.42342 0.41434
## [89] 0.40526 0.39618 0.38701 0.37761 0.36822 0.35878 0.34913 0.33937
## [97] 0.32960 0.31979 0.30998 0.30017 0.29030 0.28015 0.27000 0.25985
## [105] 0.24970 0.23915 0.22855 0.21758 0.20612 0.19441 0.18259 0.17077
## [113] 0.15858 0.14591 0.13314 0.12037 0.10760 0.09482 0.08175 0.06848
## [121] 0.05520 0.04140 0.02760 0.01380 0.00000 0.00000
##
## $FP
## [1] 1.000000 0.991935 0.983871 0.975806 0.967742 0.959677 0.951613
## [8] 0.943548 0.935484 0.927419 0.919355 0.911290 0.903226 0.895161
## [15] 0.887097 0.879032 0.870968 0.862903 0.854839 0.846774 0.838710
## [22] 0.830645 0.822581 0.814516 0.806452 0.798387 0.790323 0.782258
## [29] 0.774194 0.766129 0.758065 0.750000 0.741935 0.733871 0.725806
## [36] 0.717742 0.709677 0.701613 0.693548 0.685484 0.677419 0.669355
## [43] 0.661290 0.653226 0.645161 0.637097 0.629032 0.620968 0.612903
## [50] 0.604839 0.596774 0.588710 0.580645 0.572581 0.564516 0.556452
## [57] 0.548387 0.540323 0.532258 0.524194 0.516129 0.508065 0.500000
## [64] 0.491935 0.483871 0.475806 0.467742 0.459677 0.451613 0.443548
## [71] 0.435484 0.427419 0.419355 0.411290 0.403226 0.395161 0.387097
## [78] 0.379032 0.370968 0.362903 0.354839 0.346774 0.338710 0.330645
## [85] 0.322581 0.314516 0.306452 0.298387 0.290323 0.282258 0.274194
## [92] 0.266129 0.258065 0.250000 0.241935 0.233871 0.225806 0.217742
## [99] 0.209677 0.201613 0.193548 0.185484 0.177419 0.169355 0.161290
## [106] 0.153226 0.145161 0.137097 0.129032 0.120968 0.112903 0.104839
## [113] 0.096774 0.088710 0.080645 0.072581 0.064516 0.056452 0.048387
## [120] 0.040323 0.032258 0.024194 0.016129 0.008065 0.000000 0.000000
##
## $AUC
## [1] 0.5858

risksetROC(data.glasgow$Time/365.25*12, status = data.glasgow$DSD, marker = gg2.linpred.glasgow, predict
```



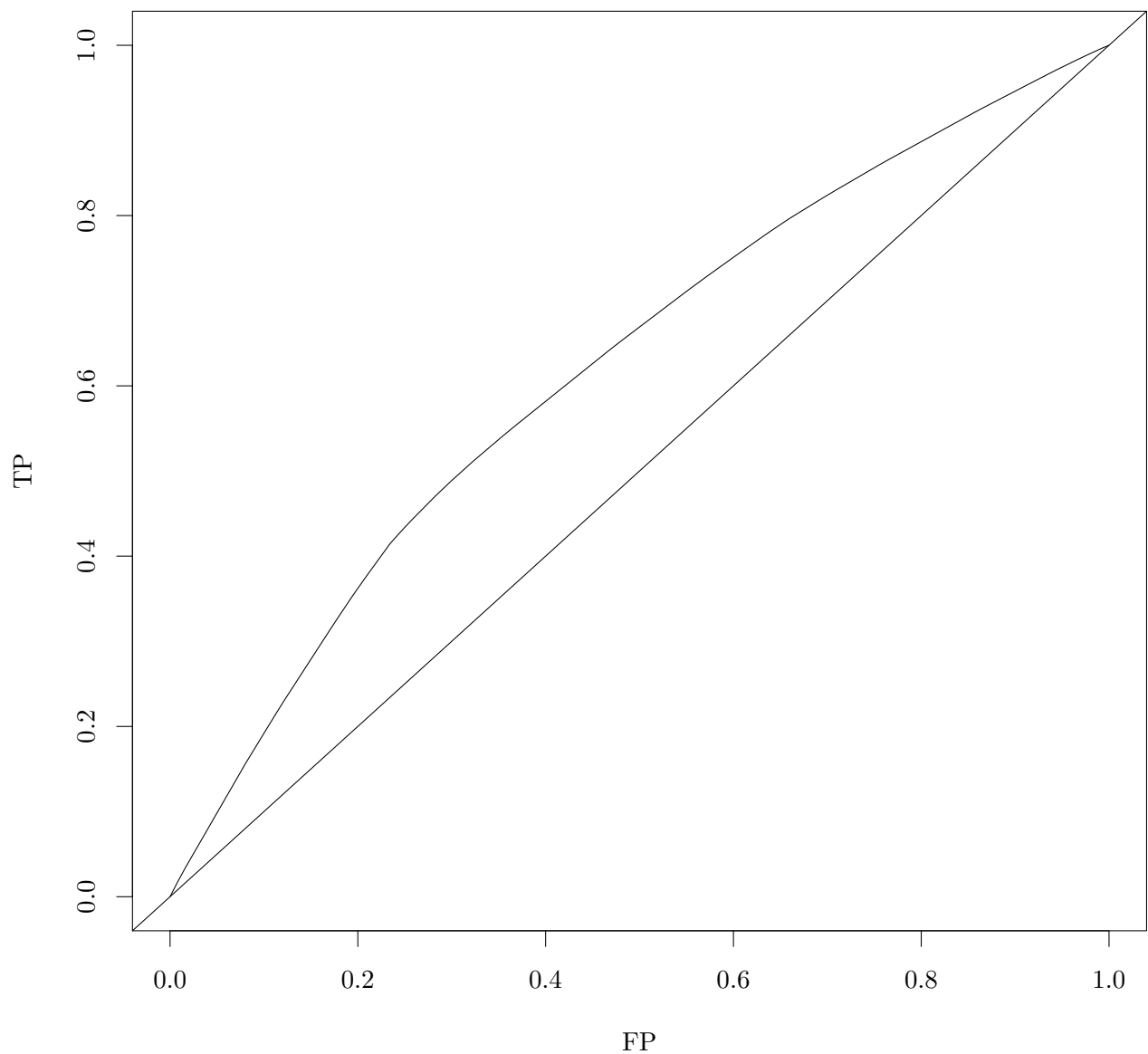
```
## $marker
## [1] -0.508607 -0.395314 -0.365103 -0.365103 -0.365103 -0.357550 -0.357550
## [8] -0.319786 -0.319786 -0.319786 -0.319786 -0.319786 -0.319786 -0.319786
## [15] -0.282022 -0.282022 -0.272976 -0.266916 -0.244258 -0.244258 -0.244258
## [22] -0.244258 -0.206494 -0.197448 -0.197448 -0.159684 -0.144578 -0.130965
## [29] -0.121919 -0.121919 -0.121919 -0.121919 -0.114367 -0.113292 -0.113292
## [36] -0.098187 -0.084155 -0.084155 -0.084155 -0.084155 -0.084155 -0.076602
## [43] -0.075528 -0.075528 -0.069050 -0.046391 -0.046391 -0.046391 -0.037764
## [50] -0.037764 -0.037764 -0.037764 -0.030211 -0.015106 0.000000 0.000000
## [57] 0.000000 0.000000 0.007553 0.029137 0.029137 0.037764 0.037764
## [64] 0.037764 0.037764 0.066901 0.066901 0.144997 0.144997 0.152550
## [71] 0.160103 0.160103 0.160103 0.164872 0.166162 0.190314 0.197867
## [78] 0.197867 0.197867 0.197867 0.217742 0.220525 0.231354 0.235631
## [85] 0.235631 0.235631 0.235631 0.235631 0.235631 0.235631 0.240400
## [92] 0.240400 0.273395 0.278164 0.278164 0.311159 0.311159 0.311159
## [99] 0.315928 0.315928 0.315928 0.315928 0.324555 0.347214 0.353693
## [106] 0.386688 0.391457 0.462216 0.484658 0.484658 0.513376 0.514869
```

```

## [113] 0.552633 0.560186 0.560186 0.560186 0.560186 0.582845 0.597950
## [120] 0.597950 0.635714 0.635714 0.635714 0.635714
##
## $TP
## [1] 1.00000 0.99570 0.99088 0.98591 0.98094 0.97597 0.97097 0.96596
## [9] 0.96077 0.95557 0.95037 0.94517 0.93998 0.93478 0.92958 0.92418
## [17] 0.91878 0.91334 0.90786 0.90225 0.89665 0.89104 0.88544 0.87961
## [25] 0.87374 0.86787 0.86177 0.85557 0.84929 0.84296 0.83662 0.83029
## [33] 0.82395 0.81757 0.81118 0.80479 0.79830 0.79173 0.78515 0.77857
## [41] 0.77199 0.76541 0.75878 0.75215 0.74551 0.73883 0.73200 0.72517
## [49] 0.71833 0.71144 0.70455 0.69766 0.69077 0.68383 0.67678 0.66962
## [57] 0.66246 0.65531 0.64815 0.64094 0.63357 0.62620 0.61877 0.61134
## [65] 0.60391 0.59648 0.58883 0.58117 0.57290 0.56463 0.55629 0.54789
## [73] 0.53949 0.53109 0.52266 0.51421 0.50555 0.49683 0.48810 0.47938
## [81] 0.47066 0.46176 0.45284 0.44382 0.43476 0.42570 0.41665 0.40759
## [89] 0.39853 0.38947 0.38041 0.37131 0.36221 0.35281 0.34335 0.33390
## [97] 0.32413 0.31437 0.30460 0.29478 0.28497 0.27515 0.26534 0.25544
## [105] 0.24531 0.23512 0.22458 0.21399 0.20263 0.19101 0.17939 0.16744
## [113] 0.15546 0.14302 0.13049 0.11796 0.10543 0.09290 0.08008 0.06707
## [121] 0.05406 0.04054 0.02703 0.01351 0.00000 0.00000
##
## $FP
## [1] 1.000000 0.991935 0.983871 0.975806 0.967742 0.959677 0.951613
## [8] 0.943548 0.935484 0.927419 0.919355 0.911290 0.903226 0.895161
## [15] 0.887097 0.879032 0.870968 0.862903 0.854839 0.846774 0.838710
## [22] 0.830645 0.822581 0.814516 0.806452 0.798387 0.790323 0.782258
## [29] 0.774194 0.766129 0.758065 0.750000 0.741935 0.733871 0.725806
## [36] 0.717742 0.709677 0.701613 0.693548 0.685484 0.677419 0.669355
## [43] 0.661290 0.653226 0.645161 0.637097 0.629032 0.620968 0.612903
## [50] 0.604839 0.596774 0.588710 0.580645 0.572581 0.564516 0.556452
## [57] 0.548387 0.540323 0.532258 0.524194 0.516129 0.508065 0.500000
## [64] 0.491935 0.483871 0.475806 0.467742 0.459677 0.451613 0.443548
## [71] 0.435484 0.427419 0.419355 0.411290 0.403226 0.395161 0.387097
## [78] 0.379032 0.370968 0.362903 0.354839 0.346774 0.338710 0.330645
## [85] 0.322581 0.314516 0.306452 0.298387 0.290323 0.282258 0.274194
## [92] 0.266129 0.258065 0.250000 0.241935 0.233871 0.225806 0.217742
## [99] 0.209677 0.201613 0.193548 0.185484 0.177419 0.169355 0.161290
## [106] 0.153226 0.145161 0.137097 0.129032 0.120968 0.112903 0.104839
## [113] 0.096774 0.088710 0.080645 0.072581 0.064516 0.056452 0.048387
## [120] 0.040323 0.032258 0.024194 0.016129 0.008065 0.000000 0.000000
##
## $AUC
## [1] 0.5815

risksetROC(data.glasgow$Time/365.25*12, status = data.glasgow$DSD, marker = cph.linpred.glasgow, predict

```



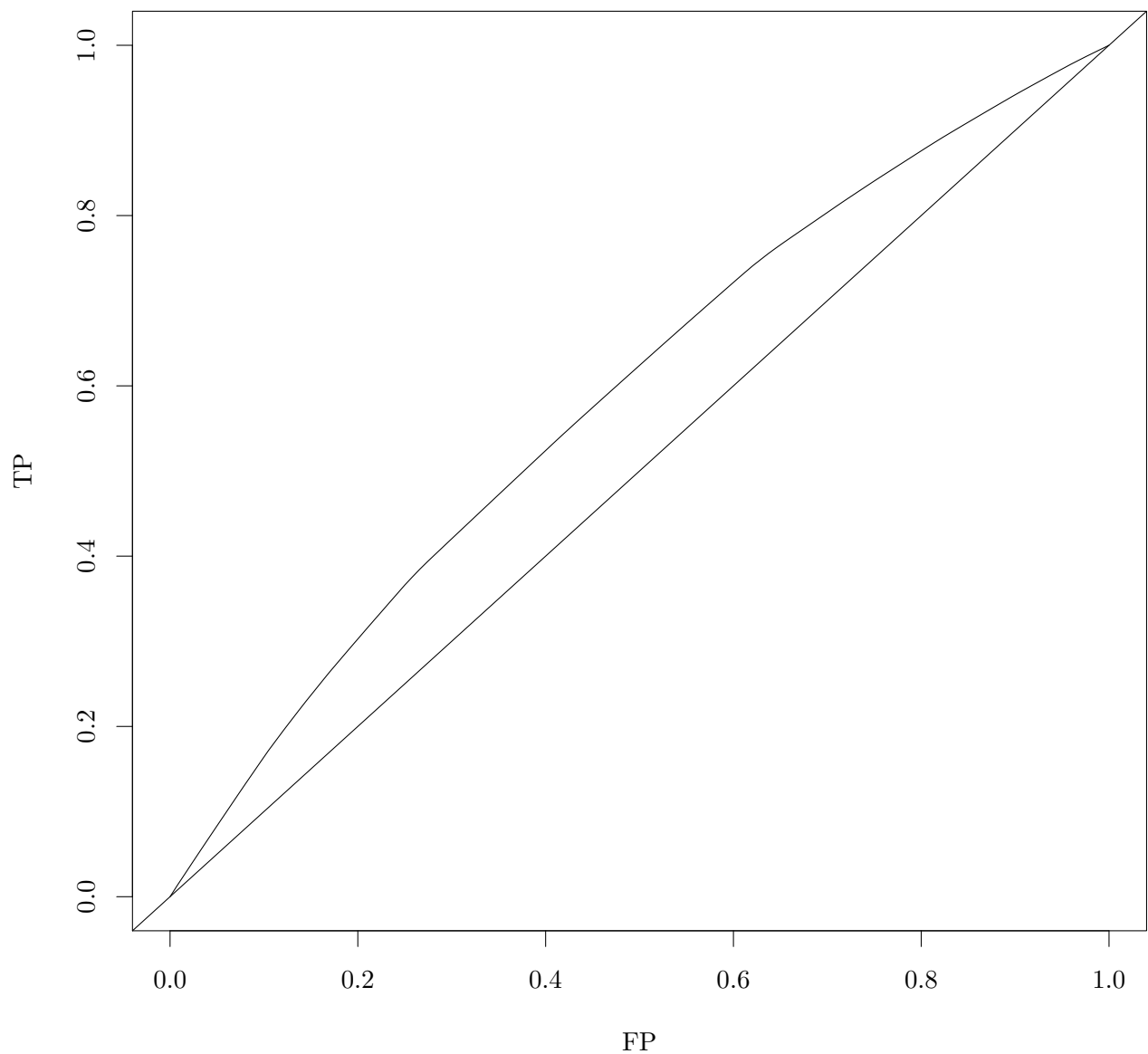
```
## $marker
## [1] -0.28807 -0.17284 -0.17284 -0.14979 -0.11523 -0.11523 -0.11523
## [8] -0.06914 -0.06914 -0.06914 -0.05761 -0.05761 -0.05761 -0.05761
## [15] -0.05761 -0.05761 -0.04609 -0.02305 0.00000 0.00000 0.00000
## [22] 0.00000 0.00000 0.00000 0.00000 0.00000 0.00000 0.00000
## [29] 0.00000 0.01152 0.05761 0.05761 0.05761 0.05761 0.05761
## [36] 0.05761 0.08066 0.09166 0.11523 0.11523 0.11523 0.11523
## [43] 0.17284 0.20689 0.20689 0.24146 0.24146 0.25298 0.25350
## [50] 0.26450 0.26450 0.26450 0.26450 0.28755 0.28807 0.31060
## [57] 0.32212 0.32212 0.32212 0.32212 0.32212 0.32212 0.32212
## [64] 0.32212 0.33364 0.35669 0.37973 0.37973 0.37973 0.37973
## [71] 0.37973 0.37973 0.37973 0.37973 0.37973 0.37973 0.37973
## [78] 0.37973 0.39125 0.40278 0.43734 0.43734 0.43734 0.43734
## [85] 0.49496 0.49496 0.49496 0.55257 0.55257 0.61019 0.61019
## [92] 0.61019 0.65364 0.68821 0.72541 0.91814 0.91814 0.91814
## [99] 0.94171 0.96423 0.99880 0.99932 1.02185 1.03337 1.03337
## [106] 1.03337 1.03337 1.03337 1.03337 1.06794 1.09098 1.09098
```

```

## [113] 1.09098 1.09098 1.14860 1.14860 1.14860 1.14860 1.14860
## [120] 1.14860 1.14860 1.14860 1.20621 1.26382
##
## $TP
## [1] 1.00000 0.99634 0.99222 0.98811 0.98390 0.97955 0.97519 0.97084
## [9] 0.96627 0.96171 0.95715 0.95254 0.94792 0.94331 0.93869 0.93408
## [17] 0.92947 0.92480 0.92002 0.91513 0.91025 0.90536 0.90047 0.89558
## [25] 0.89069 0.88581 0.88092 0.87603 0.87114 0.86626 0.86131 0.85613
## [33] 0.85096 0.84578 0.84060 0.83542 0.83024 0.82495 0.81959 0.81410
## [41] 0.80862 0.80313 0.79765 0.79184 0.78583 0.77982 0.77359 0.76737
## [49] 0.76108 0.75478 0.74841 0.74204 0.73567 0.72931 0.72279 0.71627
## [57] 0.70960 0.70286 0.69611 0.68937 0.68262 0.67588 0.66913 0.66238
## [65] 0.65564 0.64882 0.64183 0.63469 0.62754 0.62040 0.61325 0.60610
## [73] 0.59896 0.59181 0.58467 0.57752 0.57038 0.56323 0.55609 0.54886
## [81] 0.54155 0.53398 0.52641 0.51884 0.51127 0.50325 0.49523 0.48721
## [89] 0.47872 0.47023 0.46123 0.45223 0.44323 0.43384 0.42411 0.41401
## [97] 0.40177 0.38953 0.37729 0.36475 0.35193 0.33866 0.32538 0.31180
## [105] 0.29807 0.28433 0.27059 0.25685 0.24312 0.22938 0.21516 0.20061
## [113] 0.18605 0.17150 0.15695 0.14153 0.12612 0.11070 0.09529 0.07987
## [121] 0.06446 0.04904 0.03363 0.01730 0.00000 0.00000
##
## $FP
## [1] 1.000000 0.991935 0.983871 0.975806 0.967742 0.959677 0.951613
## [8] 0.943548 0.935484 0.927419 0.919355 0.911290 0.903226 0.895161
## [15] 0.887097 0.879032 0.870968 0.862903 0.854839 0.846774 0.838710
## [22] 0.830645 0.822581 0.814516 0.806452 0.798387 0.790323 0.782258
## [29] 0.774194 0.766129 0.758065 0.750000 0.741935 0.733871 0.725806
## [36] 0.717742 0.709677 0.701613 0.693548 0.685484 0.677419 0.669355
## [43] 0.661290 0.653226 0.645161 0.637097 0.629032 0.620968 0.612903
## [50] 0.604839 0.596774 0.588710 0.580645 0.572581 0.564516 0.556452
## [57] 0.548387 0.540323 0.532258 0.524194 0.516129 0.508065 0.500000
## [64] 0.491935 0.483871 0.475806 0.467742 0.459677 0.451613 0.443548
## [71] 0.435484 0.427419 0.419355 0.411290 0.403226 0.395161 0.387097
## [78] 0.379032 0.370968 0.362903 0.354839 0.346774 0.338710 0.330645
## [85] 0.322581 0.314516 0.306452 0.298387 0.290323 0.282258 0.274194
## [92] 0.266129 0.258065 0.250000 0.241935 0.233871 0.225806 0.217742
## [99] 0.209677 0.201613 0.193548 0.185484 0.177419 0.169355 0.161290
## [106] 0.153226 0.145161 0.137097 0.129032 0.120968 0.112903 0.104839
## [113] 0.096774 0.088710 0.080645 0.072581 0.064516 0.056452 0.048387
## [120] 0.040323 0.032258 0.024194 0.016129 0.008065 0.000000 0.000000
##
## $AUC
## [1] 0.6215

risksetROC(data.glasgow$Time/365.25*12, status = data.glasgow$DSD, marker = rsf.linpred.glasgow, predict

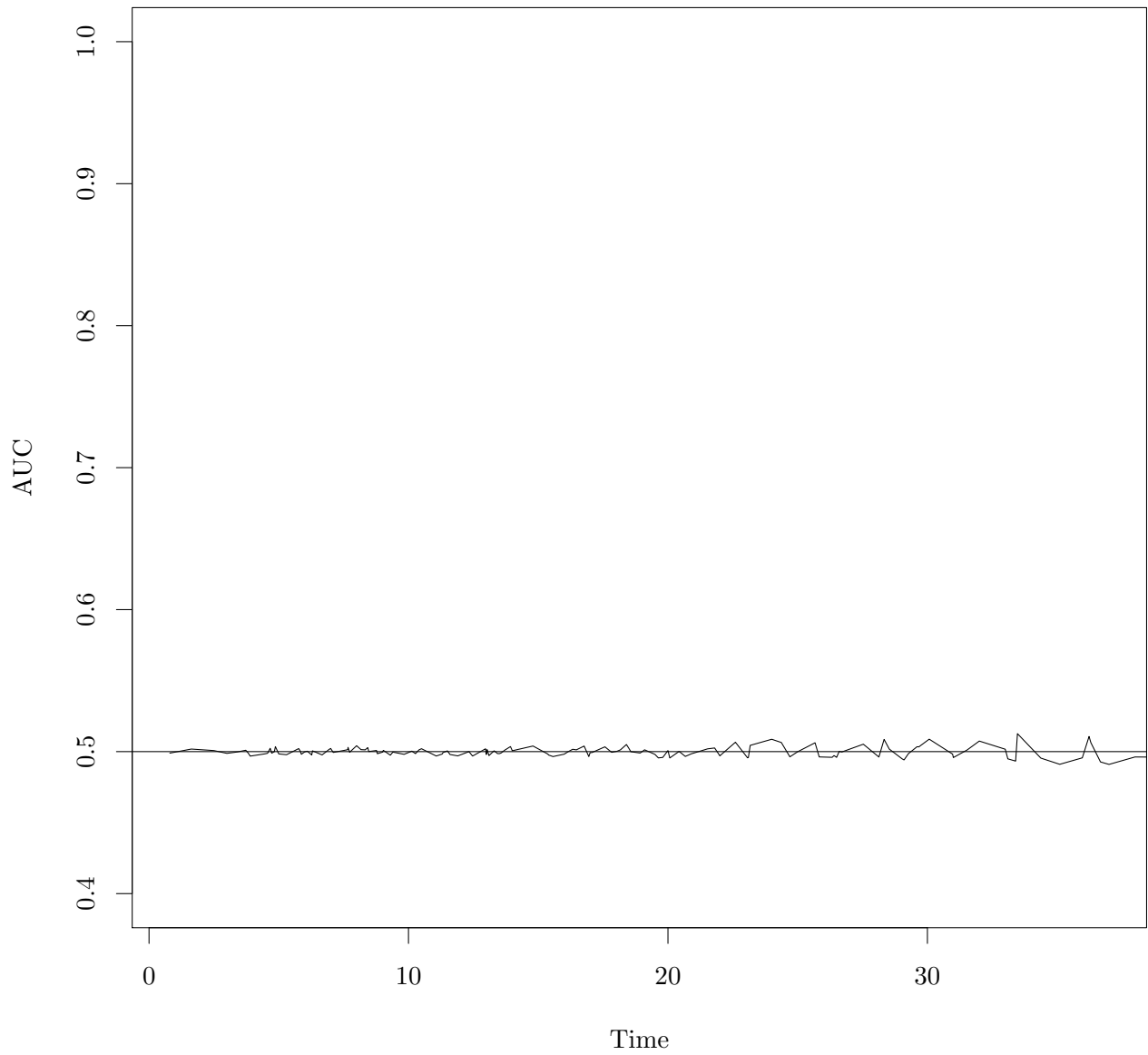
```



```
## $marker
## [1] -2.1577 -2.1537 -2.1530 -2.1121 -2.1098 -2.0627 -2.0499 -2.0478
## [9] -2.0373 -2.0360 -2.0360 -2.0240 -1.9944 -1.9856 -1.9788 -1.9738
## [17] -1.9726 -1.9667 -1.9659 -1.9648 -1.9560 -1.9471 -1.9188 -1.9079
## [25] -1.8852 -1.8844 -1.8842 -1.8828 -1.8828 -1.8797 -1.8751 -1.8586
## [33] -1.8498 -1.8468 -1.8450 -1.8187 -1.8142 -1.8135 -1.8129 -1.8123
## [41] -1.8121 -1.8121 -1.8101 -1.7773 -1.7518 -1.6846 -1.6826 -1.6050
## [49] -1.5822 -1.5722 -1.5711 -1.5697 -1.5694 -1.5689 -1.5682 -1.5616
## [57] -1.5610 -1.5580 -1.5571 -1.5538 -1.5509 -1.5507 -1.5504 -1.5500
## [65] -1.5492 -1.5469 -1.5431 -1.5419 -1.5413 -1.5413 -1.5303 -1.5300
## [73] -1.5171 -1.5061 -1.5048 -1.5033 -1.5031 -1.5025 -1.5020 -1.5014
## [81] -1.5001 -1.5001 -1.5001 -1.4991 -1.4984 -1.4982 -1.4977 -1.4972
## [89] -1.4950 -1.4892 -1.4599 -1.3967 -1.3742 -1.3034 -1.3032 -1.3029
## [97] -1.3025 -1.2972 -1.2905 -1.2897 -1.2812 -1.2784 -1.2731 -1.2278
## [105] -1.2227 -1.2221 -1.1955 -1.1766 -1.1716 -1.1460 -1.1453 -1.0732
## [113] -1.0671 -1.0650 -1.0552 -1.0467 -1.0465 -1.0430 -1.0420 -1.0378
## [121] -1.0297 -1.0276 -1.0271 -0.9954
```

```
##
## $TP
## [1] 1.00000 0.99567 0.99132 0.98697 0.98243 0.97789 0.97313 0.96830
## [9] 0.96347 0.95858 0.95369 0.94880 0.94385 0.93875 0.93360 0.92842
## [17] 0.92322 0.91800 0.91276 0.90751 0.90226 0.89696 0.89161 0.88611
## [25] 0.88055 0.87486 0.86917 0.86348 0.85778 0.85207 0.84635 0.84061
## [33] 0.83477 0.82887 0.82296 0.81704 0.81096 0.80485 0.79874 0.79263
## [41] 0.78651 0.78039 0.77427 0.76814 0.76180 0.75530 0.74835 0.74138
## [49] 0.73386 0.72615 0.71837 0.71059 0.70279 0.69499 0.68718 0.67937
## [57] 0.67151 0.66364 0.65575 0.64786 0.63993 0.63199 0.62404 0.61609
## [65] 0.60814 0.60018 0.59220 0.58419 0.57617 0.56815 0.56012 0.55201
## [73] 0.54390 0.53568 0.52737 0.51905 0.51071 0.50238 0.49404 0.48569
## [81] 0.47734 0.46898 0.46062 0.45226 0.44389 0.43552 0.42714 0.41876
## [89] 0.41037 0.40197 0.39352 0.38481 0.37554 0.36606 0.35588 0.34570
## [97] 0.33552 0.32533 0.31509 0.30478 0.29446 0.28406 0.27362 0.26313
## [105] 0.25215 0.24112 0.23008 0.21874 0.20719 0.19558 0.18366 0.17174
## [113] 0.15893 0.14604 0.13312 0.12007 0.10692 0.09376 0.08055 0.06733
## [121] 0.05406 0.04068 0.02727 0.01385 0.00000 0.00000
##
## $FP
## [1] 1.000000 0.991935 0.983871 0.975806 0.967742 0.959677 0.951613
## [8] 0.943548 0.935484 0.927419 0.919355 0.911290 0.903226 0.895161
## [15] 0.887097 0.879032 0.870968 0.862903 0.854839 0.846774 0.838710
## [22] 0.830645 0.822581 0.814516 0.806452 0.798387 0.790323 0.782258
## [29] 0.774194 0.766129 0.758065 0.750000 0.741935 0.733871 0.725806
## [36] 0.717742 0.709677 0.701613 0.693548 0.685484 0.677419 0.669355
## [43] 0.661290 0.653226 0.645161 0.637097 0.629032 0.620968 0.612903
## [50] 0.604839 0.596774 0.588710 0.580645 0.572581 0.564516 0.556452
## [57] 0.548387 0.540323 0.532258 0.524194 0.516129 0.508065 0.500000
## [64] 0.491935 0.483871 0.475806 0.467742 0.459677 0.451613 0.443548
## [71] 0.435484 0.427419 0.419355 0.411290 0.403226 0.395161 0.387097
## [78] 0.379032 0.370968 0.362903 0.354839 0.346774 0.338710 0.330645
## [85] 0.322581 0.314516 0.306452 0.298387 0.290323 0.282258 0.274194
## [92] 0.266129 0.258065 0.250000 0.241935 0.233871 0.225806 0.217742
## [99] 0.209677 0.201613 0.193548 0.185484 0.177419 0.169355 0.161290
## [106] 0.153226 0.145161 0.137097 0.129032 0.120968 0.112903 0.104839
## [113] 0.096774 0.088710 0.080645 0.072581 0.064516 0.056452 0.048387
## [120] 0.040323 0.032258 0.024194 0.016129 0.008065 0.000000 0.000000
##
## $AUC
## [1] 0.5888
```

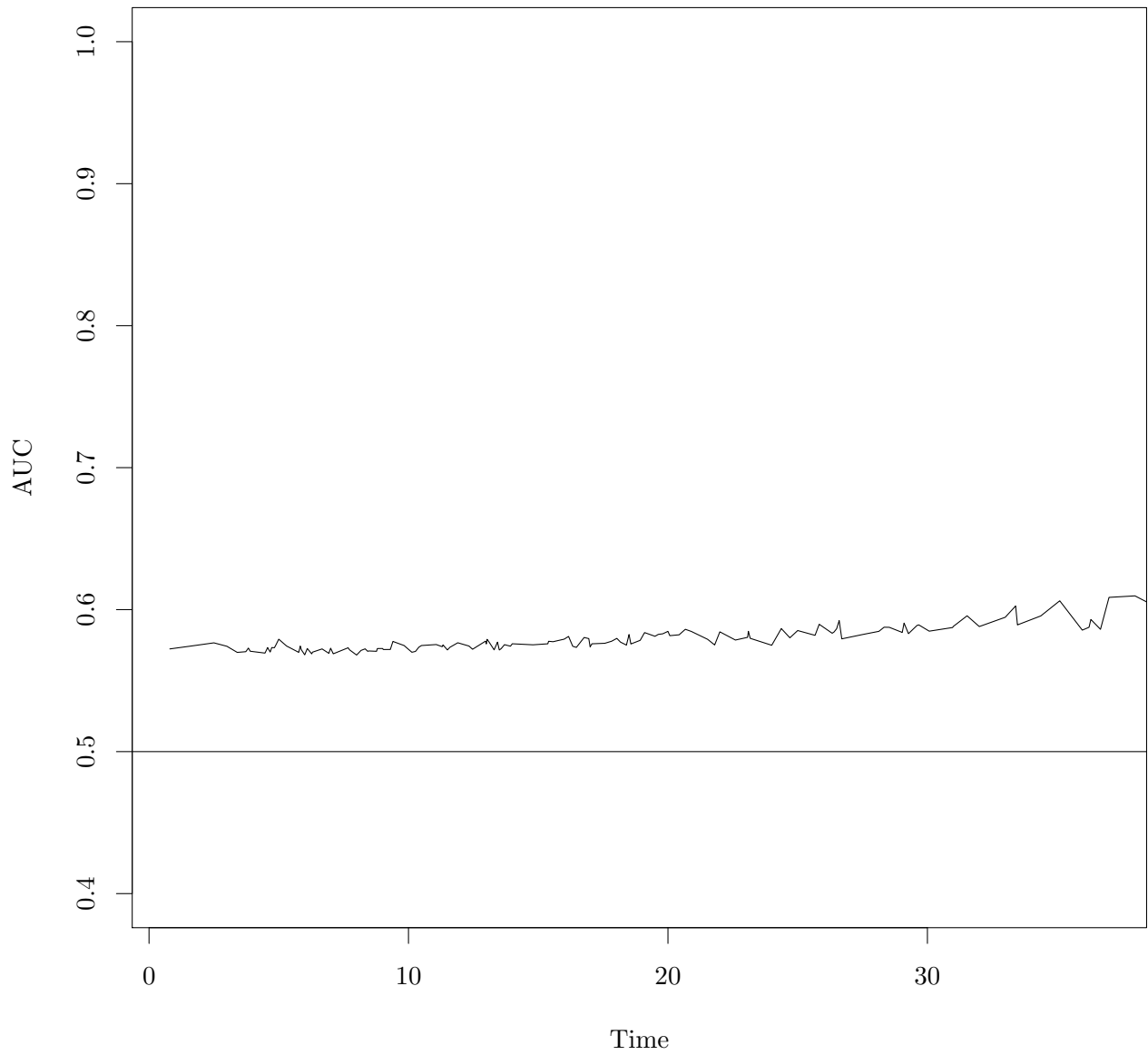
```
risksetAUC(data.glasgow$Time/365.25*12, status = data.glasgow$DSD, marker = mskcc_pre.linpred.glasgow, t
```

##	\$utimes										
##	[1]	0.80	1.63	2.50	3.00	3.40	3.73	3.83	3.90	4.47	4.57
##	[11]	4.67	4.73	4.83	4.87	5.00	5.30	5.77	5.83	5.87	6.00
##	[21]	6.10	6.27	6.30	6.67	6.93	7.00	7.10	7.66	7.67	7.73
##	[31]	8.00	8.17	8.33	8.43	8.47	8.77	8.80	9.00	9.03	9.30
##	[41]	9.40	9.83	10.13	10.27	10.40	10.50	11.07	11.30	11.33	11.50
##	[51]	11.60	11.90	12.33	12.47	12.97	13.00	13.03	13.10	13.30	13.43
##	[61]	13.50	13.57	13.70	13.93	14.00	14.80	15.37	15.40	15.57	16.00
##	[71]	16.17	16.33	16.47	16.77	16.95	17.00	17.07	17.57	17.83	18.03
##	[81]	18.17	18.40	18.50	18.57	18.93	19.10	19.50	19.63	19.80	20.00
##	[91]	20.07	20.43	20.67	20.90	21.53	21.80	22.00	22.60	23.07	23.10
##	[101]	23.17	24.00	24.37	24.70	25.00	25.67	25.83	26.33	26.40	26.50
##	[111]	26.60	26.70	27.53	28.13	28.33	28.53	29.03	29.10	29.27	29.60
##	[121]	29.67	30.07	30.97	31.00	31.53	32.00	33.00	33.10	33.40	33.47
##	[131]	34.37	35.10	35.97	36.23	36.30	36.67	37.00	38.00	39.60	41.23
##	[141]	43.07	45.37	46.67	47.43	47.73	48.00	49.00	51.00	54.90	59.00
##	[151]	63.13	65.00	67.00	70.00	77.00	85.00	85.80	90.33	93.00	94.77

```
## [161] 116.00
##
## $St
## [1] 0.99476 0.98930 0.98383 0.97834 0.97284 0.96734 0.96185 0.95086
## [9] 0.93986 0.93437 0.92887 0.92337 0.91788 0.90689 0.89589 0.89040
## [17] 0.88490 0.87940 0.87391 0.86841 0.86291 0.85742 0.85192 0.84643
## [25] 0.84093 0.83543 0.82994 0.82444 0.81894 0.81345 0.80246 0.79696
## [33] 0.79146 0.78597 0.78047 0.77497 0.76948 0.76398 0.75845 0.75291
## [41] 0.74737 0.74184 0.73630 0.73077 0.72523 0.71969 0.71416 0.70862
## [49] 0.70308 0.69755 0.69201 0.68648 0.68094 0.67540 0.66987 0.66433
## [57] 0.65880 0.65326 0.64772 0.64219 0.63665 0.63112 0.62558 0.62004
## [65] 0.61451 0.60892 0.60333 0.59775 0.59216 0.58658 0.58099 0.57540
## [73] 0.56982 0.56423 0.55864 0.55306 0.54747 0.54188 0.53630 0.53071
## [81] 0.52512 0.51954 0.51395 0.50837 0.50278 0.49719 0.49161 0.48602
## [89] 0.48043 0.46926 0.46367 0.45809 0.45250 0.44691 0.44133 0.43574
## [97] 0.43016 0.42457 0.41898 0.41340 0.40781 0.39664 0.39105 0.38546
## [105] 0.37429 0.36870 0.36312 0.35753 0.35195 0.34636 0.34077 0.33519
## [113] 0.32960 0.32401 0.31843 0.31284 0.30725 0.30167 0.29608 0.29049
## [121] 0.28491 0.27932 0.27374 0.26815 0.26256 0.25698 0.25139 0.24580
## [129] 0.24022 0.23463 0.22904 0.22332 0.21759 0.21187 0.20614 0.20041
## [137] 0.19469 0.18289 0.17679 0.17048 0.16416 0.15760 0.15103 0.14446
## [145] 0.13790 0.13133 0.12442 0.11751 0.10967 0.10184 0.09401 0.08617
## [153] 0.07834 0.07050 0.06169 0.05141 0.04113 0.03085 0.02056 0.01028
## [161] 0.00000
##
## $AUC
## [1] 0.4989 0.5018 0.5007 0.4988 0.4998 0.5010 0.4988 0.4968 0.4984 0.4989
## [11] 0.5023 0.4989 0.5000 0.5035 0.4984 0.4978 0.5021 0.5003 0.4981 0.4998
## [21] 0.5003 0.4976 0.5006 0.4977 0.5014 0.5022 0.4994 0.5014 0.5030 0.4995
## [31] 0.5041 0.5014 0.5013 0.5028 0.5001 0.5008 0.4985 0.4997 0.5009 0.4975
## [41] 0.4997 0.4981 0.5004 0.4986 0.5012 0.5020 0.4969 0.4983 0.4993 0.5005
## [51] 0.4980 0.4970 0.5000 0.4969 0.5020 0.4979 0.5014 0.4972 0.5006 0.4986
## [61] 0.4986 0.4990 0.5009 0.5036 0.5006 0.5039 0.4983 0.4976 0.4965 0.4982
## [71] 0.5001 0.5017 0.5012 0.5039 0.4965 0.4993 0.4994 0.5034 0.4995 0.5002
## [81] 0.5013 0.5050 0.5021 0.4999 0.4990 0.5013 0.4980 0.4956 0.4959 0.5007
## [91] 0.4955 0.5002 0.4966 0.4984 0.5020 0.5026 0.4970 0.5066 0.4956 0.4959
## [101] 0.5044 0.5087 0.5064 0.4963 0.4999 0.5062 0.4963 0.4960 0.4972 0.4960
## [111] 0.5002 0.4997 0.5052 0.4962 0.5086 0.5018 0.4949 0.4941 0.4986 0.5034
## [121] 0.5034 0.5088 0.4983 0.4958 0.5012 0.5074 0.5017 0.4949 0.4933 0.5127
## [131] 0.4955 0.4911 0.4956 0.5107 0.5063 0.4927 0.4910 0.4962 0.4960 0.4900
## [141] 0.4942 0.4897 0.4932 0.5232 0.5198 0.4847 0.5216 0.4930 0.5204 0.4821
## [151] 0.4758 0.5357 0.4924 0.4517 0.4380 0.4171 0.4504 0.6255 0.5000 0.7500
## [161] 0.0000
##
## $Cindex
## [1] 0.5

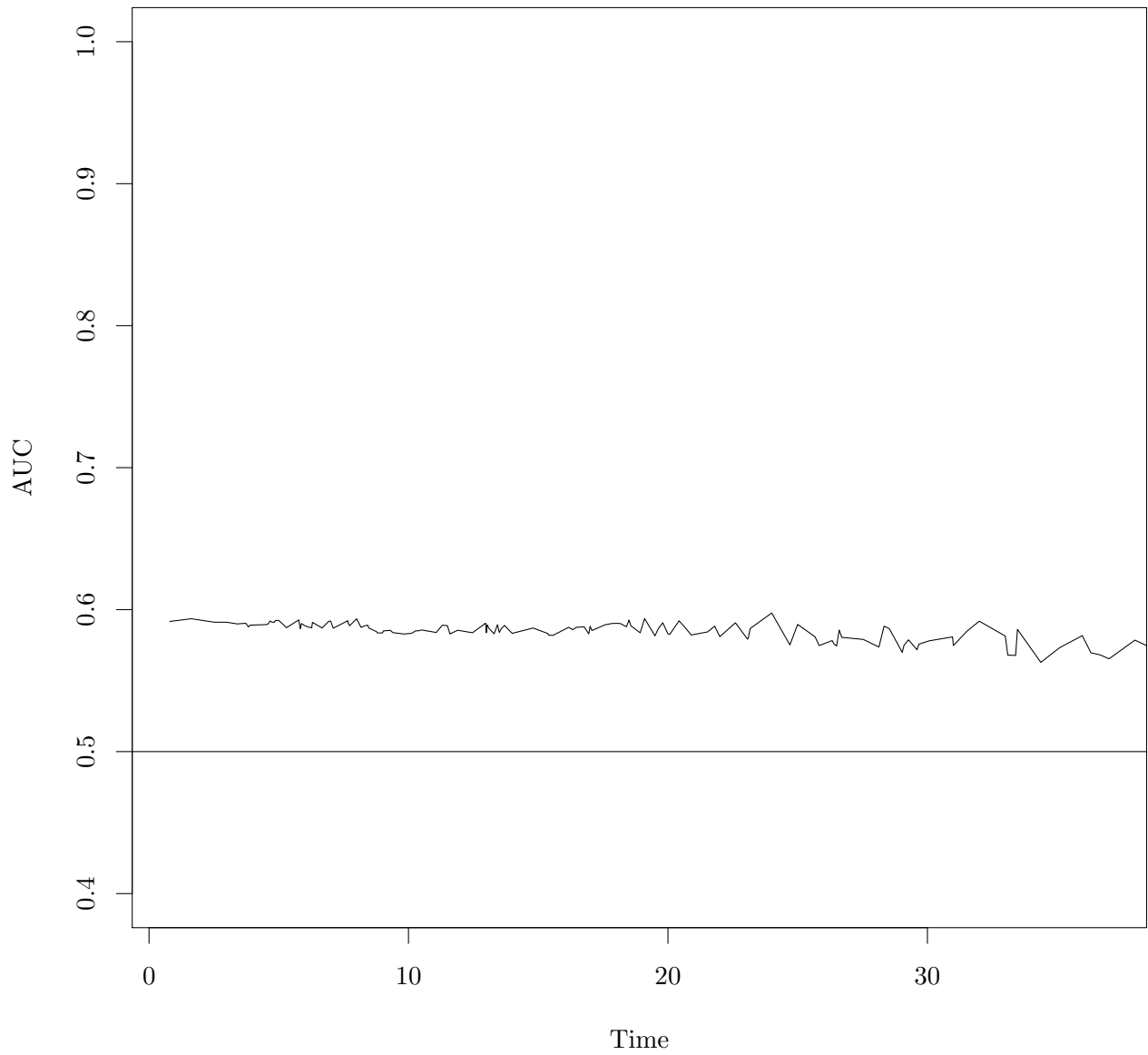
risksetAUC(data.glasgow$Time/365.25*12, status = data.glasgow$DSD, marker = mskcc_post.linpred.glasgow,
```



##	\$utimes										
##	[1]	0.80	1.63	2.50	3.00	3.40	3.73	3.83	3.90	4.47	4.57
##	[11]	4.67	4.73	4.83	4.87	5.00	5.30	5.77	5.83	5.87	6.00
##	[21]	6.10	6.27	6.30	6.67	6.93	7.00	7.10	7.66	7.67	7.73
##	[31]	8.00	8.17	8.33	8.43	8.47	8.77	8.80	9.00	9.03	9.30
##	[41]	9.40	9.83	10.13	10.27	10.40	10.50	11.07	11.30	11.33	11.50
##	[51]	11.60	11.90	12.33	12.47	12.97	13.00	13.03	13.10	13.30	13.43
##	[61]	13.50	13.57	13.70	13.93	14.00	14.80	15.37	15.40	15.57	16.00
##	[71]	16.17	16.33	16.47	16.77	16.95	17.00	17.07	17.57	17.83	18.03
##	[81]	18.17	18.40	18.50	18.57	18.93	19.10	19.50	19.63	19.80	20.00
##	[91]	20.07	20.43	20.67	20.90	21.53	21.80	22.00	22.60	23.07	23.10
##	[101]	23.17	24.00	24.37	24.70	25.00	25.67	25.83	26.33	26.40	26.50
##	[111]	26.60	26.70	27.53	28.13	28.33	28.53	29.03	29.10	29.27	29.60
##	[121]	29.67	30.07	30.97	31.00	31.53	32.00	33.00	33.10	33.40	33.47
##	[131]	34.37	35.10	35.97	36.23	36.30	36.67	37.00	38.00	39.60	41.23
##	[141]	43.07	45.37	46.67	47.43	47.73	48.00	49.00	51.00	54.90	59.00
##	[151]	63.13	65.00	67.00	70.00	77.00	85.00	85.80	90.33	93.00	94.77

```
## [161] 116.00
##
## $St
## [1] 0.99476 0.98930 0.98383 0.97834 0.97284 0.96734 0.96185 0.95086
## [9] 0.93986 0.93437 0.92887 0.92337 0.91788 0.90689 0.89589 0.89040
## [17] 0.88490 0.87940 0.87391 0.86841 0.86291 0.85742 0.85192 0.84643
## [25] 0.84093 0.83543 0.82994 0.82444 0.81894 0.81345 0.80246 0.79696
## [33] 0.79146 0.78597 0.78047 0.77497 0.76948 0.76398 0.75845 0.75291
## [41] 0.74737 0.74184 0.73630 0.73077 0.72523 0.71969 0.71416 0.70862
## [49] 0.70308 0.69755 0.69201 0.68648 0.68094 0.67540 0.66987 0.66433
## [57] 0.65880 0.65326 0.64772 0.64219 0.63665 0.63112 0.62558 0.62004
## [65] 0.61451 0.60892 0.60333 0.59775 0.59216 0.58658 0.58099 0.57540
## [73] 0.56982 0.56423 0.55864 0.55306 0.54747 0.54188 0.53630 0.53071
## [81] 0.52512 0.51954 0.51395 0.50837 0.50278 0.49719 0.49161 0.48602
## [89] 0.48043 0.46926 0.46367 0.45809 0.45250 0.44691 0.44133 0.43574
## [97] 0.43016 0.42457 0.41898 0.41340 0.40781 0.39664 0.39105 0.38546
## [105] 0.37429 0.36870 0.36312 0.35753 0.35195 0.34636 0.34077 0.33519
## [113] 0.32960 0.32401 0.31843 0.31284 0.30725 0.30167 0.29608 0.29049
## [121] 0.28491 0.27932 0.27374 0.26815 0.26256 0.25698 0.25139 0.24580
## [129] 0.24022 0.23463 0.22904 0.22332 0.21759 0.21187 0.20614 0.20041
## [137] 0.19469 0.18289 0.17679 0.17048 0.16416 0.15760 0.15103 0.14446
## [145] 0.13790 0.13133 0.12442 0.11751 0.10967 0.10184 0.09401 0.08617
## [153] 0.07834 0.07050 0.06169 0.05141 0.04113 0.03085 0.02056 0.01028
## [161] 0.00000
##
## $AUC
## [1] 0.5723 0.5744 0.5766 0.5742 0.5699 0.5704 0.5729 0.5707 0.5694 0.5733
## [11] 0.5701 0.5733 0.5732 0.5744 0.5792 0.5744 0.5699 0.5743 0.5718 0.5682
## [21] 0.5726 0.5689 0.5701 0.5723 0.5692 0.5729 0.5689 0.5730 0.5732 0.5717
## [31] 0.5680 0.5713 0.5724 0.5706 0.5709 0.5707 0.5726 0.5726 0.5719 0.5719
## [41] 0.5776 0.5747 0.5700 0.5706 0.5736 0.5747 0.5754 0.5739 0.5752 0.5716
## [51] 0.5735 0.5767 0.5744 0.5721 0.5778 0.5758 0.5791 0.5773 0.5717 0.5771
## [61] 0.5716 0.5725 0.5753 0.5743 0.5760 0.5752 0.5759 0.5777 0.5774 0.5792
## [71] 0.5811 0.5742 0.5734 0.5804 0.5796 0.5738 0.5759 0.5763 0.5778 0.5798
## [81] 0.5771 0.5750 0.5825 0.5758 0.5784 0.5838 0.5812 0.5826 0.5830 0.5847
## [91] 0.5817 0.5823 0.5862 0.5847 0.5791 0.5751 0.5844 0.5786 0.5805 0.5848
## [101] 0.5798 0.5749 0.5867 0.5802 0.5853 0.5819 0.5897 0.5834 0.5842 0.5865
## [111] 0.5923 0.5794 0.5826 0.5847 0.5876 0.5876 0.5839 0.5905 0.5831 0.5889
## [121] 0.5892 0.5848 0.5874 0.5882 0.5957 0.5881 0.5946 0.5966 0.6026 0.5892
## [131] 0.5956 0.6062 0.5856 0.5876 0.5931 0.5861 0.6086 0.6097 0.5945 0.5881
## [141] 0.6132 0.5807 0.5967 0.5913 0.5844 0.6111 0.5856 0.6234 0.6160 0.6236
## [151] 0.6229 0.5656 0.6111 0.6573 0.5917 0.5836 0.5309 0.4725 0.7439 0.2936
## [161] 0.0000
##
## $Cindex
## [1] 0.576
```

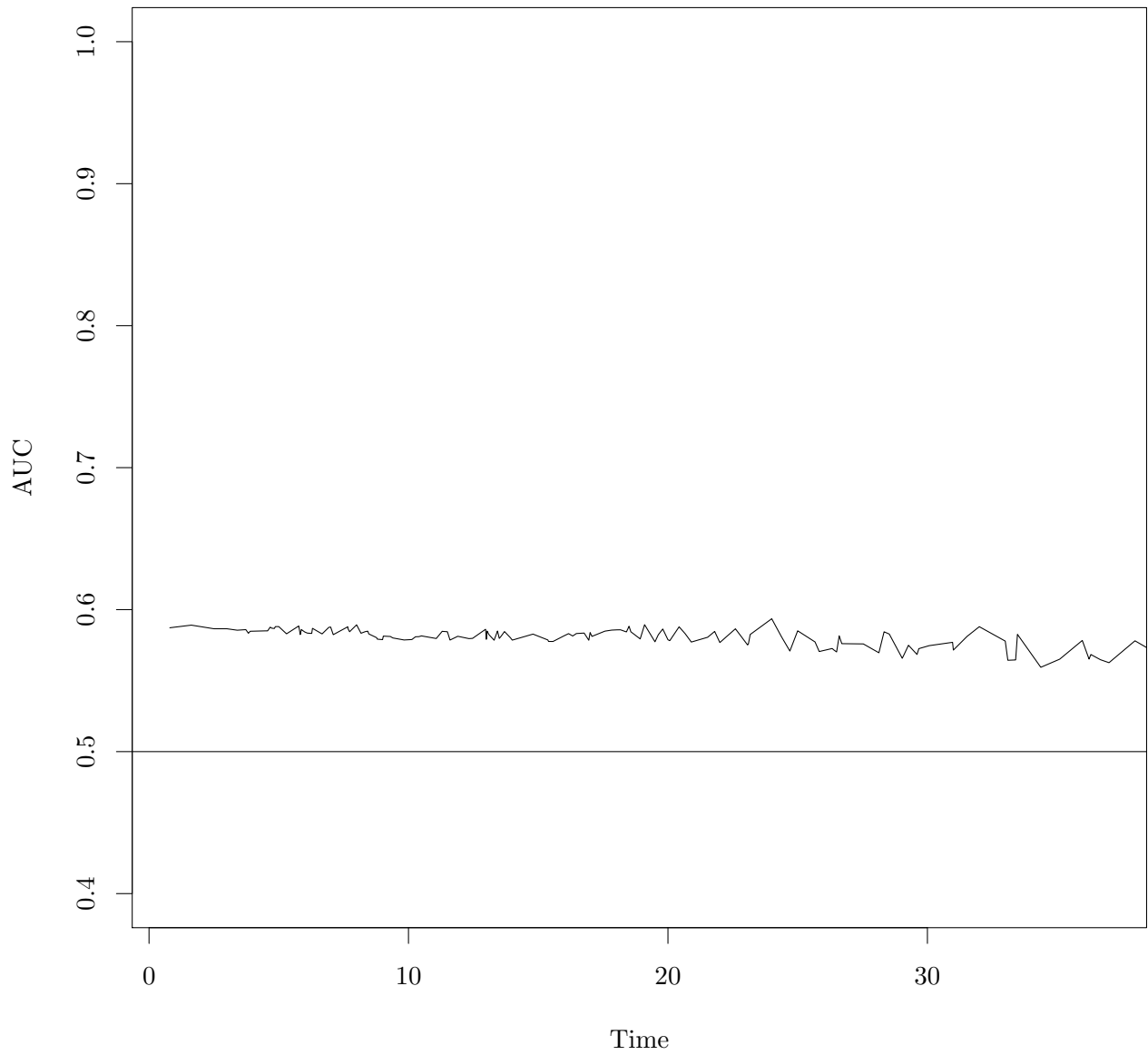
```
risksetAUC(data.glasgow$Time/365.25*12, status = data.glasgow$DSD, marker = gg.linpred.glasgow, tmax = 3
```



##	\$utimes										
##	[1]	0.80	1.63	2.50	3.00	3.40	3.73	3.83	3.90	4.47	4.57
##	[11]	4.67	4.73	4.83	4.87	5.00	5.30	5.77	5.83	5.87	6.00
##	[21]	6.10	6.27	6.30	6.67	6.93	7.00	7.10	7.66	7.67	7.73
##	[31]	8.00	8.17	8.33	8.43	8.47	8.77	8.80	9.00	9.03	9.30
##	[41]	9.40	9.83	10.13	10.27	10.40	10.50	11.07	11.30	11.33	11.50
##	[51]	11.60	11.90	12.33	12.47	12.97	13.00	13.03	13.10	13.30	13.43
##	[61]	13.50	13.57	13.70	13.93	14.00	14.80	15.37	15.40	15.57	16.00
##	[71]	16.17	16.33	16.47	16.77	16.95	17.00	17.07	17.57	17.83	18.03
##	[81]	18.17	18.40	18.50	18.57	18.93	19.10	19.50	19.63	19.80	20.00
##	[91]	20.07	20.43	20.67	20.90	21.53	21.80	22.00	22.60	23.07	23.10
##	[101]	23.17	24.00	24.37	24.70	25.00	25.67	25.83	26.33	26.40	26.50
##	[111]	26.60	26.70	27.53	28.13	28.33	28.53	29.03	29.10	29.27	29.60
##	[121]	29.67	30.07	30.97	31.00	31.53	32.00	33.00	33.10	33.40	33.47
##	[131]	34.37	35.10	35.97	36.23	36.30	36.67	37.00	38.00	39.60	41.23
##	[141]	43.07	45.37	46.67	47.43	47.73	48.00	49.00	51.00	54.90	59.00
##	[151]	63.13	65.00	67.00	70.00	77.00	85.00	85.80	90.33	93.00	94.77

```
## [161] 116.00
##
## $St
## [1] 0.99476 0.98930 0.98383 0.97834 0.97284 0.96734 0.96185 0.95086
## [9] 0.93986 0.93437 0.92887 0.92337 0.91788 0.90689 0.89589 0.89040
## [17] 0.88490 0.87940 0.87391 0.86841 0.86291 0.85742 0.85192 0.84643
## [25] 0.84093 0.83543 0.82994 0.82444 0.81894 0.81345 0.80246 0.79696
## [33] 0.79146 0.78597 0.78047 0.77497 0.76948 0.76398 0.75845 0.75291
## [41] 0.74737 0.74184 0.73630 0.73077 0.72523 0.71969 0.71416 0.70862
## [49] 0.70308 0.69755 0.69201 0.68648 0.68094 0.67540 0.66987 0.66433
## [57] 0.65880 0.65326 0.64772 0.64219 0.63665 0.63112 0.62558 0.62004
## [65] 0.61451 0.60892 0.60333 0.59775 0.59216 0.58658 0.58099 0.57540
## [73] 0.56982 0.56423 0.55864 0.55306 0.54747 0.54188 0.53630 0.53071
## [81] 0.52512 0.51954 0.51395 0.50837 0.50278 0.49719 0.49161 0.48602
## [89] 0.48043 0.46926 0.46367 0.45809 0.45250 0.44691 0.44133 0.43574
## [97] 0.43016 0.42457 0.41898 0.41340 0.40781 0.39664 0.39105 0.38546
## [105] 0.37429 0.36870 0.36312 0.35753 0.35195 0.34636 0.34077 0.33519
## [113] 0.32960 0.32401 0.31843 0.31284 0.30725 0.30167 0.29608 0.29049
## [121] 0.28491 0.27932 0.27374 0.26815 0.26256 0.25698 0.25139 0.24580
## [129] 0.24022 0.23463 0.22904 0.22332 0.21759 0.21187 0.20614 0.20041
## [137] 0.19469 0.18289 0.17679 0.17048 0.16416 0.15760 0.15103 0.14446
## [145] 0.13790 0.13133 0.12442 0.11751 0.10967 0.10184 0.09401 0.08617
## [153] 0.07834 0.07050 0.06169 0.05141 0.04113 0.03085 0.02056 0.01028
## [161] 0.00000
##
## $AUC
## [1] 0.5917 0.5936 0.5912 0.5911 0.5899 0.5904 0.5879 0.5891 0.5894 0.5896
## [11] 0.5920 0.5913 0.5911 0.5923 0.5924 0.5873 0.5928 0.5866 0.5902 0.5888
## [21] 0.5880 0.5872 0.5910 0.5871 0.5918 0.5920 0.5869 0.5922 0.5907 0.5887
## [31] 0.5935 0.5875 0.5887 0.5891 0.5871 0.5844 0.5836 0.5836 0.5850 0.5854
## [41] 0.5838 0.5828 0.5833 0.5851 0.5851 0.5857 0.5839 0.5890 0.5890 0.5887
## [51] 0.5829 0.5855 0.5841 0.5837 0.5905 0.5837 0.5893 0.5868 0.5830 0.5893
## [61] 0.5840 0.5863 0.5889 0.5845 0.5833 0.5870 0.5832 0.5820 0.5819 0.5859
## [71] 0.5876 0.5859 0.5875 0.5879 0.5829 0.5883 0.5853 0.5893 0.5902 0.5903
## [81] 0.5902 0.5879 0.5926 0.5886 0.5837 0.5937 0.5816 0.5866 0.5907 0.5829
## [91] 0.5826 0.5921 0.5872 0.5821 0.5843 0.5883 0.5810 0.5907 0.5792 0.5804
## [101] 0.5867 0.5976 0.5858 0.5752 0.5896 0.5809 0.5747 0.5782 0.5758 0.5744
## [111] 0.5857 0.5805 0.5790 0.5737 0.5884 0.5866 0.5699 0.5749 0.5788 0.5717
## [121] 0.5756 0.5780 0.5808 0.5747 0.5849 0.5919 0.5814 0.5680 0.5677 0.5861
## [131] 0.5629 0.5733 0.5817 0.5723 0.5696 0.5681 0.5654 0.5785 0.5647 0.5790
## [141] 0.5606 0.5945 0.5721 0.5641 0.5621 0.5586 0.5937 0.5741 0.5670 0.5571
## [151] 0.6063 0.5946 0.5687 0.5307 0.5078 0.5116 0.4663 0.5029 0.7187 0.7616
## [161] 0.0000
##
## $Cindex
## [1] 0.587

risksetAUC(data.glasgow$Time/365.25*12, status = data.glasgow$DSD, marker = gg2.linpred.glasgow, tmax =
```



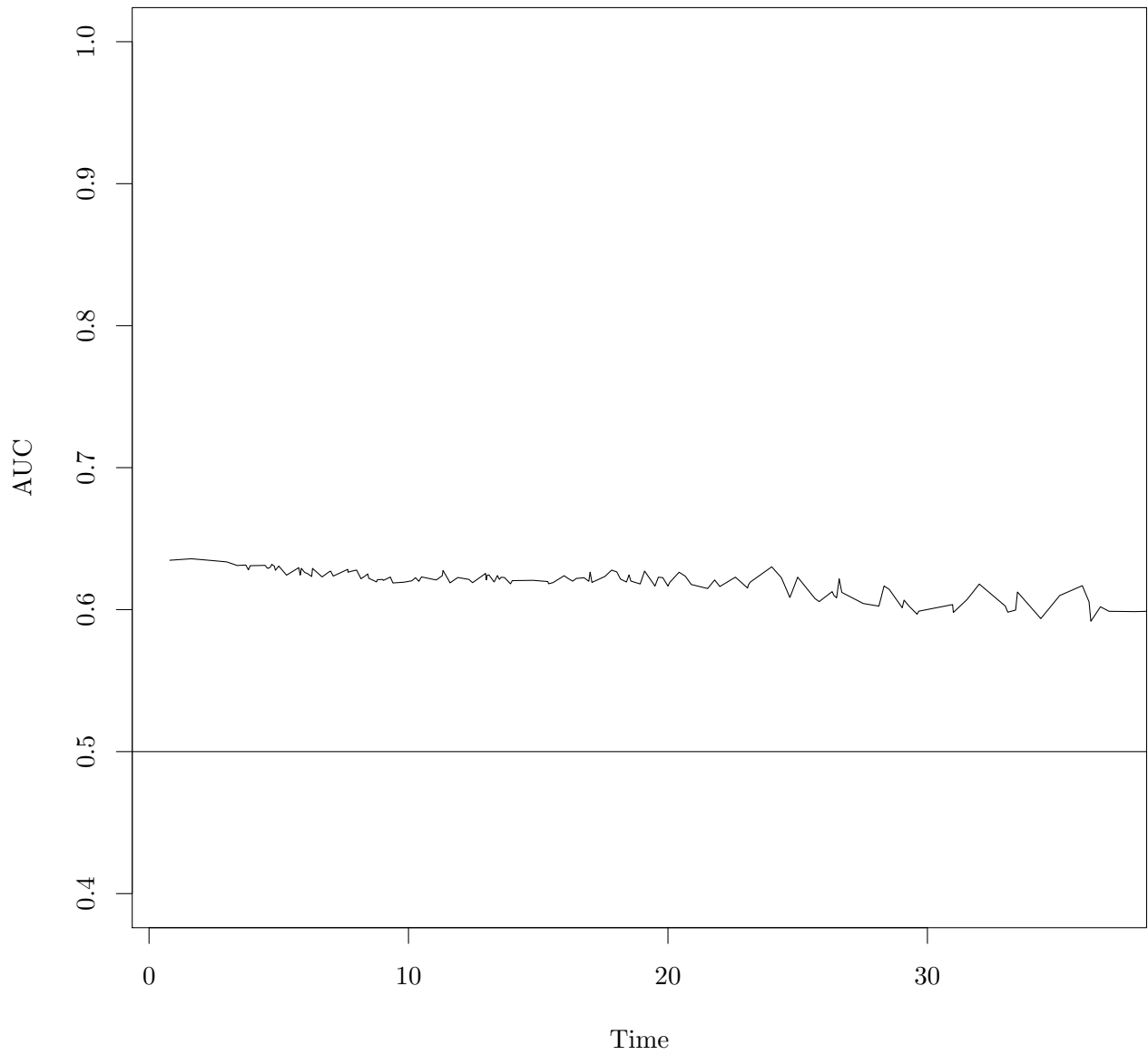
##	\$utimes										
##	[1]	0.80	1.63	2.50	3.00	3.40	3.73	3.83	3.90	4.47	4.57
##	[11]	4.67	4.73	4.83	4.87	5.00	5.30	5.77	5.83	5.87	6.00
##	[21]	6.10	6.27	6.30	6.67	6.93	7.00	7.10	7.66	7.67	7.73
##	[31]	8.00	8.17	8.33	8.43	8.47	8.77	8.80	9.00	9.03	9.30
##	[41]	9.40	9.83	10.13	10.27	10.40	10.50	11.07	11.30	11.33	11.50
##	[51]	11.60	11.90	12.33	12.47	12.97	13.00	13.03	13.10	13.30	13.43
##	[61]	13.50	13.57	13.70	13.93	14.00	14.80	15.37	15.40	15.57	16.00
##	[71]	16.17	16.33	16.47	16.77	16.95	17.00	17.07	17.57	17.83	18.03
##	[81]	18.17	18.40	18.50	18.57	18.93	19.10	19.50	19.63	19.80	20.00
##	[91]	20.07	20.43	20.67	20.90	21.53	21.80	22.00	22.60	23.07	23.10
##	[101]	23.17	24.00	24.37	24.70	25.00	25.67	25.83	26.33	26.40	26.50
##	[111]	26.60	26.70	27.53	28.13	28.33	28.53	29.03	29.10	29.27	29.60
##	[121]	29.67	30.07	30.97	31.00	31.53	32.00	33.00	33.10	33.40	33.47
##	[131]	34.37	35.10	35.97	36.23	36.30	36.67	37.00	38.00	39.60	41.23
##	[141]	43.07	45.37	46.67	47.43	47.73	48.00	49.00	51.00	54.90	59.00
##	[151]	63.13	65.00	67.00	70.00	77.00	85.00	85.80	90.33	93.00	94.77

```

## [161] 116.00
##
## $St
## [1] 0.99476 0.98930 0.98383 0.97834 0.97284 0.96734 0.96185 0.95086
## [9] 0.93986 0.93437 0.92887 0.92337 0.91788 0.90689 0.89589 0.89040
## [17] 0.88490 0.87940 0.87391 0.86841 0.86291 0.85742 0.85192 0.84643
## [25] 0.84093 0.83543 0.82994 0.82444 0.81894 0.81345 0.80246 0.79696
## [33] 0.79146 0.78597 0.78047 0.77497 0.76948 0.76398 0.75845 0.75291
## [41] 0.74737 0.74184 0.73630 0.73077 0.72523 0.71969 0.71416 0.70862
## [49] 0.70308 0.69755 0.69201 0.68648 0.68094 0.67540 0.66987 0.66433
## [57] 0.65880 0.65326 0.64772 0.64219 0.63665 0.63112 0.62558 0.62004
## [65] 0.61451 0.60892 0.60333 0.59775 0.59216 0.58658 0.58099 0.57540
## [73] 0.56982 0.56423 0.55864 0.55306 0.54747 0.54188 0.53630 0.53071
## [81] 0.52512 0.51954 0.51395 0.50837 0.50278 0.49719 0.49161 0.48602
## [89] 0.48043 0.46926 0.46367 0.45809 0.45250 0.44691 0.44133 0.43574
## [97] 0.43016 0.42457 0.41898 0.41340 0.40781 0.39664 0.39105 0.38546
## [105] 0.37429 0.36870 0.36312 0.35753 0.35195 0.34636 0.34077 0.33519
## [113] 0.32960 0.32401 0.31843 0.31284 0.30725 0.30167 0.29608 0.29049
## [121] 0.28491 0.27932 0.27374 0.26815 0.26256 0.25698 0.25139 0.24580
## [129] 0.24022 0.23463 0.22904 0.22332 0.21759 0.21187 0.20614 0.20041
## [137] 0.19469 0.18289 0.17679 0.17048 0.16416 0.15760 0.15103 0.14446
## [145] 0.13790 0.13133 0.12442 0.11751 0.10967 0.10184 0.09401 0.08617
## [153] 0.07834 0.07050 0.06169 0.05141 0.04113 0.03085 0.02056 0.01028
## [161] 0.00000
##
## $AUC
## [1] 0.5872 0.5891 0.5865 0.5865 0.5855 0.5859 0.5834 0.5848 0.5850 0.5851
## [11] 0.5877 0.5869 0.5867 0.5880 0.5880 0.5830 0.5885 0.5824 0.5860 0.5843
## [21] 0.5835 0.5832 0.5868 0.5829 0.5875 0.5877 0.5824 0.5879 0.5865 0.5844
## [31] 0.5893 0.5834 0.5845 0.5849 0.5829 0.5803 0.5792 0.5789 0.5814 0.5811
## [41] 0.5800 0.5786 0.5789 0.5809 0.5810 0.5815 0.5797 0.5847 0.5847 0.5844
## [51] 0.5786 0.5812 0.5796 0.5798 0.5862 0.5791 0.5850 0.5824 0.5785 0.5850
## [61] 0.5798 0.5813 0.5846 0.5802 0.5785 0.5828 0.5786 0.5776 0.5776 0.5816
## [71] 0.5831 0.5814 0.5832 0.5835 0.5785 0.5839 0.5812 0.5848 0.5856 0.5858
## [81] 0.5858 0.5843 0.5883 0.5844 0.5794 0.5894 0.5774 0.5824 0.5864 0.5788
## [91] 0.5781 0.5879 0.5829 0.5772 0.5805 0.5846 0.5768 0.5865 0.5751 0.5758
## [101] 0.5825 0.5936 0.5811 0.5708 0.5851 0.5772 0.5705 0.5726 0.5715 0.5702
## [111] 0.5815 0.5760 0.5759 0.5696 0.5844 0.5828 0.5657 0.5683 0.5749 0.5684
## [121] 0.5725 0.5746 0.5770 0.5715 0.5812 0.5880 0.5778 0.5643 0.5646 0.5826
## [131] 0.5594 0.5651 0.5783 0.5652 0.5684 0.5647 0.5626 0.5780 0.5611 0.5759
## [141] 0.5573 0.5910 0.5591 0.5624 0.5586 0.5554 0.5895 0.5671 0.5626 0.5428
## [151] 0.6005 0.5901 0.5644 0.5257 0.5028 0.5057 0.4610 0.5008 0.7164 0.7613
## [161] 0.0000
##
## $Cindex
## [1] 0.5827

risksetAUC(data.glasgow$Time/365.25*12, status = data.glasgow$DSD, marker = cph.linpred.glasgow, tmax =

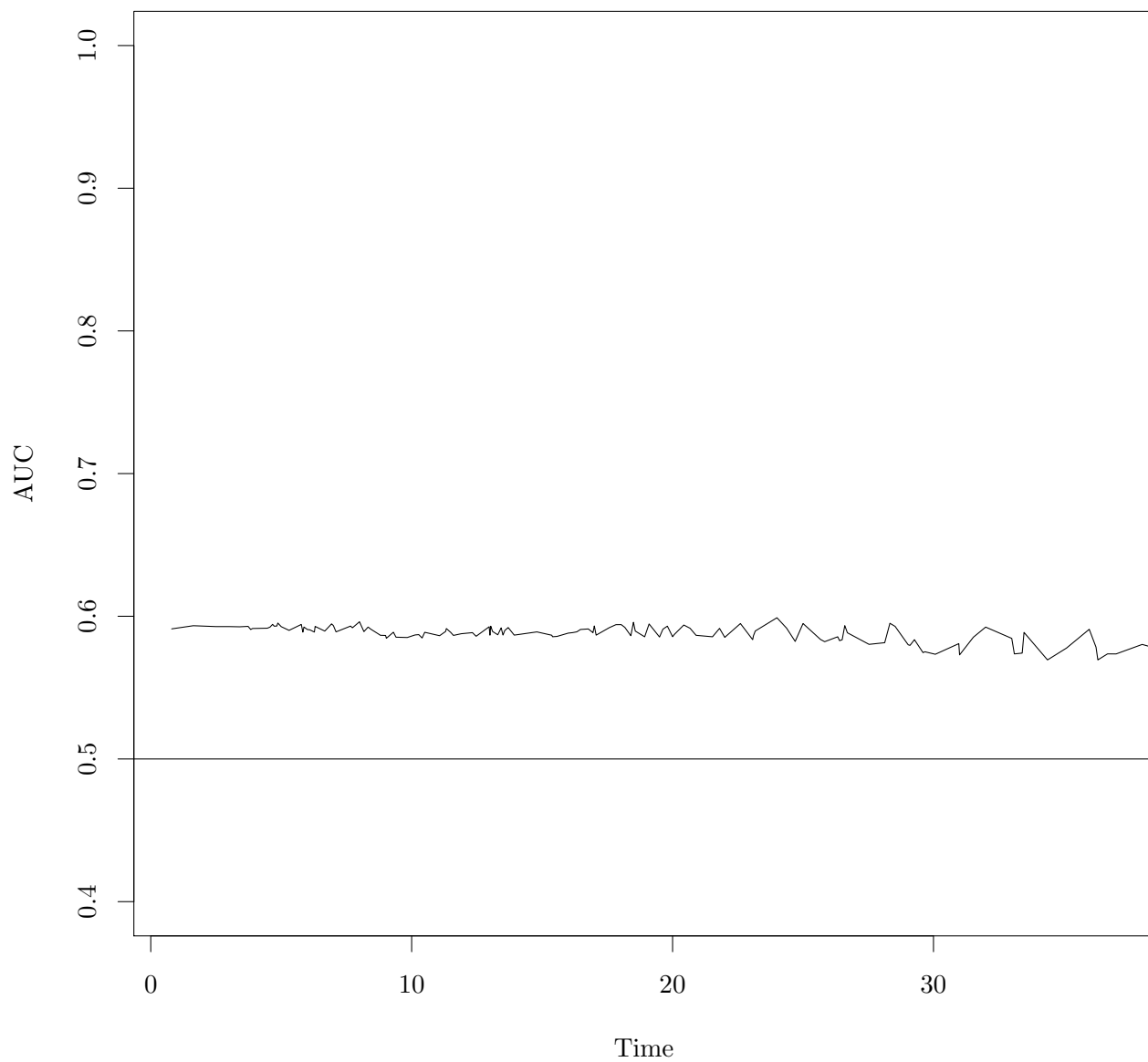
```

```
## $utimes
## [1] 0.80 1.63 2.50 3.00 3.40 3.73 3.83 3.90 4.47 4.57
## [11] 4.67 4.73 4.83 4.87 5.00 5.30 5.77 5.83 5.87 6.00
## [21] 6.10 6.27 6.30 6.67 6.93 7.00 7.10 7.66 7.67 7.73
## [31] 8.00 8.17 8.33 8.43 8.47 8.77 8.80 9.00 9.03 9.30
## [41] 9.40 9.83 10.13 10.27 10.40 10.50 11.07 11.30 11.33 11.50
## [51] 11.60 11.90 12.33 12.47 12.97 13.00 13.03 13.10 13.30 13.43
## [61] 13.50 13.57 13.70 13.93 14.00 14.80 15.37 15.40 15.57 16.00
## [71] 16.17 16.33 16.47 16.77 16.95 17.00 17.07 17.57 17.83 18.03
## [81] 18.17 18.40 18.50 18.57 18.93 19.10 19.50 19.63 19.80 20.00
## [91] 20.07 20.43 20.67 20.90 21.53 21.80 22.00 22.60 23.07 23.10
## [101] 23.17 24.00 24.37 24.70 25.00 25.67 25.83 26.33 26.40 26.50
## [111] 26.60 26.70 27.53 28.13 28.33 28.53 29.03 29.10 29.27 29.60
## [121] 29.67 30.07 30.97 31.00 31.53 32.00 33.00 33.10 33.40 33.47
## [131] 34.37 35.10 35.97 36.23 36.30 36.67 37.00 38.00 39.60 41.23
## [141] 43.07 45.37 46.67 47.43 47.73 48.00 49.00 51.00 54.90 59.00
## [151] 63.13 65.00 67.00 70.00 77.00 85.00 85.80 90.33 93.00 94.77
```

```
## [161] 116.00
##
## $St
## [1] 0.99476 0.98930 0.98383 0.97834 0.97284 0.96734 0.96185 0.95086
## [9] 0.93986 0.93437 0.92887 0.92337 0.91788 0.90689 0.89589 0.89040
## [17] 0.88490 0.87940 0.87391 0.86841 0.86291 0.85742 0.85192 0.84643
## [25] 0.84093 0.83543 0.82994 0.82444 0.81894 0.81345 0.80246 0.79696
## [33] 0.79146 0.78597 0.78047 0.77497 0.76948 0.76398 0.75845 0.75291
## [41] 0.74737 0.74184 0.73630 0.73077 0.72523 0.71969 0.71416 0.70862
## [49] 0.70308 0.69755 0.69201 0.68648 0.68094 0.67540 0.66987 0.66433
## [57] 0.65880 0.65326 0.64772 0.64219 0.63665 0.63112 0.62558 0.62004
## [65] 0.61451 0.60892 0.60333 0.59775 0.59216 0.58658 0.58099 0.57540
## [73] 0.56982 0.56423 0.55864 0.55306 0.54747 0.54188 0.53630 0.53071
## [81] 0.52512 0.51954 0.51395 0.50837 0.50278 0.49719 0.49161 0.48602
## [89] 0.48043 0.46926 0.46367 0.45809 0.45250 0.44691 0.44133 0.43574
## [97] 0.43016 0.42457 0.41898 0.41340 0.40781 0.39664 0.39105 0.38546
## [105] 0.37429 0.36870 0.36312 0.35753 0.35195 0.34636 0.34077 0.33519
## [113] 0.32960 0.32401 0.31843 0.31284 0.30725 0.30167 0.29608 0.29049
## [121] 0.28491 0.27932 0.27374 0.26815 0.26256 0.25698 0.25139 0.24580
## [129] 0.24022 0.23463 0.22904 0.22332 0.21759 0.21187 0.20614 0.20041
## [137] 0.19469 0.18289 0.17679 0.17048 0.16416 0.15760 0.15103 0.14446
## [145] 0.13790 0.13133 0.12442 0.11751 0.10967 0.10184 0.09401 0.08617
## [153] 0.07834 0.07050 0.06169 0.05141 0.04113 0.03085 0.02056 0.01028
## [161] 0.00000
##
## $AUC
## [1] 0.6348 0.6358 0.6345 0.6336 0.6311 0.6314 0.6280 0.6309 0.6312 0.6290
## [11] 0.6297 0.6319 0.6306 0.6277 0.6307 0.6243 0.6295 0.6243 0.6291 0.6262
## [21] 0.6255 0.6234 0.6290 0.6231 0.6265 0.6271 0.6236 0.6284 0.6263 0.6267
## [31] 0.6279 0.6218 0.6237 0.6251 0.6221 0.6195 0.6211 0.6213 0.6206 0.6230
## [41] 0.6188 0.6193 0.6203 0.6225 0.6199 0.6230 0.6209 0.6239 0.6276 0.6223
## [51] 0.6189 0.6226 0.6213 0.6190 0.6255 0.6209 0.6242 0.6245 0.6195 0.6240
## [61] 0.6213 0.6228 0.6226 0.6182 0.6204 0.6206 0.6198 0.6182 0.6190 0.6239
## [71] 0.6217 0.6201 0.6220 0.6225 0.6200 0.6265 0.6192 0.6234 0.6278 0.6266
## [81] 0.6215 0.6195 0.6244 0.6201 0.6181 0.6272 0.6166 0.6228 0.6225 0.6166
## [91] 0.6192 0.6263 0.6235 0.6177 0.6149 0.6209 0.6163 0.6229 0.6152 0.6174
## [101] 0.6194 0.6301 0.6226 0.6085 0.6229 0.6077 0.6057 0.6127 0.6099 0.6084
## [111] 0.6217 0.6121 0.6043 0.6025 0.6167 0.6142 0.6013 0.6067 0.6029 0.5968
## [121] 0.5989 0.6003 0.6036 0.5980 0.6071 0.6180 0.6025 0.5982 0.5997 0.6124
## [131] 0.5937 0.6099 0.6169 0.6055 0.5918 0.6020 0.5988 0.5986 0.5994 0.6199
## [141] 0.5977 0.6297 0.6181 0.5967 0.5940 0.6054 0.6296 0.6304 0.6070 0.6401
## [151] 0.6681 0.6143 0.5833 0.5562 0.5800 0.5561 0.5162 0.5436 0.7619 0.7673
## [161] 0.0000
##
## $Cindex
## [1] 0.6229

risksetAUC(data.glasgow$Time/365.25*12, status = data.glasgow$DSD, marker = rsf.linpred.glasgow, tmax =
```



##	\$utimes										
##	[1]	0.80	1.63	2.50	3.00	3.40	3.73	3.83	3.90	4.47	4.57
##	[11]	4.67	4.73	4.83	4.87	5.00	5.30	5.77	5.83	5.87	6.00
##	[21]	6.10	6.27	6.30	6.67	6.93	7.00	7.10	7.66	7.67	7.73
##	[31]	8.00	8.17	8.33	8.43	8.47	8.77	8.80	9.00	9.03	9.30
##	[41]	9.40	9.83	10.13	10.27	10.40	10.50	11.07	11.30	11.33	11.50
##	[51]	11.60	11.90	12.33	12.47	12.97	13.00	13.03	13.10	13.30	13.43
##	[61]	13.50	13.57	13.70	13.93	14.00	14.80	15.37	15.40	15.57	16.00
##	[71]	16.17	16.33	16.47	16.77	16.95	17.00	17.07	17.57	17.83	18.03
##	[81]	18.17	18.40	18.50	18.57	18.93	19.10	19.50	19.63	19.80	20.00
##	[91]	20.07	20.43	20.67	20.90	21.53	21.80	22.00	22.60	23.07	23.10
##	[101]	23.17	24.00	24.37	24.70	25.00	25.67	25.83	26.33	26.40	26.50
##	[111]	26.60	26.70	27.53	28.13	28.33	28.53	29.03	29.10	29.27	29.60
##	[121]	29.67	30.07	30.97	31.00	31.53	32.00	33.00	33.10	33.40	33.47
##	[131]	34.37	35.10	35.97	36.23	36.30	36.67	37.00	38.00	39.60	41.23
##	[141]	43.07	45.37	46.67	47.43	47.73	48.00	49.00	51.00	54.90	59.00
##	[151]	63.13	65.00	67.00	70.00	77.00	85.00	85.80	90.33	93.00	94.77

```

## [161] 116.00
##
## $St
## [1] 0.99476 0.98930 0.98383 0.97834 0.97284 0.96734 0.96185 0.95086
## [9] 0.93986 0.93437 0.92887 0.92337 0.91788 0.90689 0.89589 0.89040
## [17] 0.88490 0.87940 0.87391 0.86841 0.86291 0.85742 0.85192 0.84643
## [25] 0.84093 0.83543 0.82994 0.82444 0.81894 0.81345 0.80246 0.79696
## [33] 0.79146 0.78597 0.78047 0.77497 0.76948 0.76398 0.75845 0.75291
## [41] 0.74737 0.74184 0.73630 0.73077 0.72523 0.71969 0.71416 0.70862
## [49] 0.70308 0.69755 0.69201 0.68648 0.68094 0.67540 0.66987 0.66433
## [57] 0.65880 0.65326 0.64772 0.64219 0.63665 0.63112 0.62558 0.62004
## [65] 0.61451 0.60892 0.60333 0.59775 0.59216 0.58658 0.58099 0.57540
## [73] 0.56982 0.56423 0.55864 0.55306 0.54747 0.54188 0.53630 0.53071
## [81] 0.52512 0.51954 0.51395 0.50837 0.50278 0.49719 0.49161 0.48602
## [89] 0.48043 0.46926 0.46367 0.45809 0.45250 0.44691 0.44133 0.43574
## [97] 0.43016 0.42457 0.41898 0.41340 0.40781 0.39664 0.39105 0.38546
## [105] 0.37429 0.36870 0.36312 0.35753 0.35195 0.34636 0.34077 0.33519
## [113] 0.32960 0.32401 0.31843 0.31284 0.30725 0.30167 0.29608 0.29049
## [121] 0.28491 0.27932 0.27374 0.26815 0.26256 0.25698 0.25139 0.24580
## [129] 0.24022 0.23463 0.22904 0.22332 0.21759 0.21187 0.20614 0.20041
## [137] 0.19469 0.18289 0.17679 0.17048 0.16416 0.15760 0.15103 0.14446
## [145] 0.13790 0.13133 0.12442 0.11751 0.10967 0.10184 0.09401 0.08617
## [153] 0.07834 0.07050 0.06169 0.05141 0.04113 0.03085 0.02056 0.01028
## [161] 0.00000
##
## $AUC
## [1] 0.5912 0.5934 0.5928 0.5928 0.5926 0.5929 0.5907 0.5914 0.5917 0.5924
## [11] 0.5943 0.5931 0.5931 0.5953 0.5927 0.5901 0.5943 0.5889 0.5925 0.5908
## [21] 0.5905 0.5889 0.5929 0.5896 0.5947 0.5935 0.5891 0.5931 0.5929 0.5919
## [31] 0.5961 0.5893 0.5925 0.5910 0.5905 0.5871 0.5867 0.5866 0.5846 0.5888
## [41] 0.5853 0.5851 0.5869 0.5872 0.5848 0.5888 0.5864 0.5893 0.5914 0.5886
## [51] 0.5866 0.5878 0.5885 0.5860 0.5926 0.5868 0.5931 0.5893 0.5870 0.5919
## [61] 0.5868 0.5901 0.5921 0.5868 0.5870 0.5890 0.5867 0.5857 0.5859 0.5882
## [71] 0.5885 0.5891 0.5908 0.5911 0.5885 0.5932 0.5868 0.5920 0.5941 0.5942
## [81] 0.5922 0.5864 0.5958 0.5896 0.5856 0.5946 0.5855 0.5910 0.5931 0.5857
## [91] 0.5873 0.5939 0.5916 0.5867 0.5856 0.5915 0.5852 0.5949 0.5836 0.5863
## [101] 0.5897 0.5990 0.5917 0.5824 0.5949 0.5838 0.5822 0.5856 0.5829 0.5835
## [111] 0.5934 0.5884 0.5803 0.5815 0.5951 0.5929 0.5800 0.5796 0.5836 0.5745
## [121] 0.5751 0.5734 0.5808 0.5729 0.5853 0.5924 0.5845 0.5736 0.5742 0.5887
## [131] 0.5694 0.5777 0.5909 0.5783 0.5694 0.5736 0.5736 0.5803 0.5721 0.5825
## [141] 0.5727 0.6051 0.5843 0.5746 0.5651 0.5766 0.6048 0.6004 0.5725 0.5879
## [151] 0.6248 0.6103 0.5687 0.5463 0.5708 0.5377 0.4885 0.5096 0.7256 0.7552
## [161] 0.0000
##
## $Cindex
## [1] 0.5897

```